Designing a supply chain network integrating financial dimensions

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RÉSUMÉ EN FRANÇAIS

La mondialisation de l'économie se caractérise par une concurrence intense sur des marchés fluctuants et des préoccupations environnementales croissantes dans un contexte d'augmentation du coût de l'énergie. Les entreprises doivent améliorer continuellement leurs opérations de production et de logistique tout en réduisant leurs coûts.

Le problème de conception de chaines logistiques (en anglais Supply Chain Network Design, SCND) consiste à recherche le nombre et la localisation optimale des unités logistiques nécessaires au fonctionnement de l'entreprise. Concrètement, il s'agit de déterminer les lieux d'implantation des sites de production et de distribution, mais aussi leur capacité et les autres acteurs de la chaine logistique avec les ils sont connectés. Les décisions de localisation sont d'ordre stratégiques, dans la mesure où elles impactent la vie de l'entreprise sur une longue durée, et à un niveau global. De même, ces décisions ont un impact financier très fort, et sur une longue durée. Pourtant, les modèles mathématiques de localisation étudiés par la communauté scientifique ignorent le plus souvent la dimension financière de cette décision, Cependant, les considérations financières sont généralement omises dans la plupart des modèles mathématiques SCND. Cette thèse contribue à combler le fossé entre les domaines scientifiques des sciences de gestion et de la finance.

Traditionnellement, les problèmes de conception de réseau logistique visent à optimiser les décisions stratégiques telles que « où » et « quand » localiser les installations, comment définir la capacité des installations et comment connecter de manière optimale toutes les installations d'un réseau logistique donné. Le problème de localisation de sites est reconnu comme étant le cœur des modèles de type SCND.

Dans cette thèse, nous cherchons donc à intégrer la dimension financière dans un problème de localisation pertinent, mais suffisamment proche des modèles minimalistes, de manière à pouvoir interpréter les solutions obtenues. Nous adoptons donc les hypothèses suivantes:

- la chaine logistique comporte deux échelons : des sites de production à localiser parmi un ensemble de sites candidats, et un nombre plus élevé de sites clients, dont la demande est déterministe ;

- un modèle multi-périodique, de manière à pouvoir mesurer l'impact des investissements et de leur financement sur un horizon de temps suffisamment grand ;
- un produit unique, des flux de marchandises simples, allant directement des sites de production aux sites clients par un mode de transport unique ;
- un modèle orienté profit : il n'est pas obligatoire de satisfaire toute la demande. Cela permet notamment de trouver plus facilement des solution réalisables.

Comme suggéré par la liste précédente, il existe de nombreuses variantes de problèmes SCND. Selon ces variantes, les variables de décision peuvent concerner le nombre, la localisation et la capacité des sites, les flux de matières produites, transformées, stockées et transportées dans le réseau logistique. Dans les applications en logistique, presque tous les modèles concernent des emplacements discrets, avec une variable de décision clé associée à chaque emplacement candidat, valant 1 lorsque le site candidat est sélectionné et 0 sinon.

Dans la plupart des travaux qui mentionnent l'intégration des aspects financiers dans les modèles de localisation, la question financière apparaît à travers des contraintes budgétaires, des calculs d'exposition au risque financier (faillite) ou logistique (rupture de stock, retard). Très peu de travaux considèrent explicitement des objectifs ou des contraintes émanant du monde de la finance, alors que la théorie financière interroge la relation entre la valeur de l'entreprise (liée à son activité économique) et le choix de son financement. Cette question a été initiée par les deux théorèmes fondateurs de Modigliani & Miller. L'enjeu initial est donc d'identifier des outils et indicateurs financiers pertinents à intégrer dans les modèles de type SCND.

Le chapitre 1 passe en revue les variantes du problème SCND et les principales méthodes de résolution. En ce qui concerne les méthodes de résolution, une revue des algorithmes exacts et approchés pour résoudre des problèmes d'optimisation combinatoire à objectif unique et à objectifs multiples. Les solveurs de programmation linéaire en nombre entiers se montrent généralement efficaces pour résoudre les modèles de base ainsi que des instance de taille modeste de modèles étendus. L'état de l'art montre donc la nécessité de développer des heuristiques et métaheuristiques performantes pour les modèles complexes de localisation.

Le chapitre 2 tente d'identifier un indicateur financier approprié pour utiliser dans les modèles SCND. Nous passons en revue les principaux indicateurs financiers pouvant être implémentés au sein d'un modèle mathématique. Une comparaison est établie pour

mettre en évidence les différences entre les indicateurs financiers examinés. Cette comparaison nous amène à choisir la Valeur Actuelle Ajustée (en anglais Adjusted Present Value, APV). En effet, APV intègre à la fois les décisions logistiques et financières traditionnelles et permet aux décideurs de trouver des solutions de compromis entre les priorités logistiques et financières. Contrairement à d'autres indicateurs, APV permet également d'optimisation la structure du capital dans un modèle multi-périodique sujet à des variations de la structure du capital. Enfin, cet indicateur est également plus adapté à l'évaluation de la détresse financière, compte tenu des coûts de faillite directs et indirects.

Le chapitre 3 présente de manière étendue la formulation mathématique du problème étudié dans cette thèse. Il détermine la conception optimale du réseau ainsi que la structure optimale du capital de l'entreprise. La fonction objectif à maximiser est la valeur d'APV. Le modèle mathématique formulé contient plusieurs termes non linéaires. Un ensemble de procédures de linéarisation est appliqué de telle sorte que le modèle final est formulé comme un modèle MILP. De plus, un horizon de planification étendu est défini pour saisir les impacts à long terme des décisions financières. Pour estimer la probabilité de faillite, deux méthodes sont étudiées : la méthode du Z-score d'Altman et la méthode du ratio d'endettement. Enfin, un exemple montre comment l'intégration des décisions financières et logistiques peut influencer la configuration de la chiane logistique.

Le chapitre 4 est consacré aux expériences numériques sur le modèle présenté au chapitre 3. Ce chapitre présente 60 nouvelles instances générés aléatoirement. Toutes les expérimentations sont effectuées avec le solveur IBM Cplex.

Deux approches de solutions sont proposées pour mieux décrire l'impact de l'intégration des décisions financières et logistiques. La première approche, dite approche intégrée, résout l'ensemble du modèle en une seule étape. La seconde approchée, dite séquentielle, décompose le modèle en un sous-problèmes logistique et un sous-problème financier, et optimise séquentiellement les décisions correspondantes. Les résultats numériques indiquent que l'approche intégrée améliore légèrement la valeur de l'APV. En outre, avec cette approche, on observe que les investissement financés sont soit plus élevés, soit anticipés par rapport à l'approche séquentielle. En contrepartie, cette approche trouve des solutions où la valeur de rendement des capitaux propres (ROE) est moindre. Enfin, les tests numériques montrent que pour les approches intégrées et séquentielles, les instances de taille réaliste peuvent être résolues de manière optimale par le solveur, l'approche séquentielle étant légèrement plus rapide.

Le chapitre 5 décrit une métaheuristique de recherche à voisinage large (en anglais

Large Neighboorhood Search, LNS) proposée pour résoudre le modèle SCND dans un temps de calcul raisonnable lorsque la taille des instances est trop grande pour permettre une résolution optimale avec un solveur de programmation linéaire en nombre entiers. Chaque itération du LNS consiste en trois décisions séquentielles : la localisation des sites, les flux de marchandises et les décisions financières. Nous avons d'abord défini la valeur des décisions de localisation car celles-ci ont un impact plus global que les autres décisions. Ces variables sont définies à l'aide des opérateurs de destruction et de réparation du LNS. Ensuite, un modèle mathématique inspiré du problème d'affectation généralisé (GAP) est formulé pour définir les flux de produits. Pour résoudre ce modèle, deux méthodes différentes sont proposées et comparées : une heuristique gloutonne et un modèle relaxé résolu à l'aide de Cplex. Enfin, les décisions financières sont fixées en proposant une méthode heuristique efficace. Après avoir détaillé la méthode de résolution, nous présentons des expériences numériques validant les performances de l'algorithme. Les résultats numériques sur un jeu de 60 instances générées aléatoirement révèlent la stabilité de l'algorithme LNS ainsi que sa capacité à trouver des solutions de haute qualité dans un temps raisonnable.

Le chapitre 6 prolonge le travail en abordant un problème d'optimisation bi-objectif. Les décisions logistiques et financières sont ici considérées comme deux objectifs antagonistes. Cela permet d'étudier en profondeur les impacts des décisions financières sur la décision logistique. Une méthode epsilon-contrainte est tout d'abord implémentée pour servir de base de comparaison. Son temps de calcul s'avère très élevé. Nous proposons donc une méthode de recherche locale multi-directionnelle (en anglais Multi-Directional Local Search, MDLS) qui réutilise le LNS décrit au chapitre 5. Par rapport à la méthode epsilon-contrainte, les résultats numériques indiquent le bon comportement de MDLS en termes de temps de calcul et du nombre de solutions non dominées trouvée. La performance de MDLS est évaluée en utilisant deux mesures de performance classiques en optimisation multi-objectif. Là encore, la comparaison révèle la meilleure performance de MDLS par rapport à epsilon contrainte, en particulier lorsque la taille des instances augmente.

Le manuscrit est conclu par un aperçu de ses contributions et une proposition d'orientations de recherche futures. Ce travail est destiné à être progressivement étendu afin d'intégrer des fonctionnalités plus réalistes et des chaînes d'approvisionnement complexes. Une autre piste de développement est l'intégration de décision tactiques dans les modèles mathématiques étudiés. Enfin, le risque et l'incertitude sont intrinsèquement associés aux décisions financières. Cependant, l'incertitude ne se manifeste pas uniquement dans les

décisions financières. Les paramètres logistiques tels que le coût du transport et la demande prévue peuvent également être sujets à des incertitudes. Par conséquent, la prise en compte de ces risques est une direction de recherche naturelle.

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INTRODUCTION

The globalization of economy goes along with intense competition in unstable markets, rising environmental concerns in parallel with energy cost increase, and fierce competition on technology, quality and customer relationship management. In this competitive context, many companies need to continuously improving their operations while reducing their costs. This is particularly true in the field of Supply Chain Management (SCM), which supports any business in streamlining its operations and keeping ahead of competitors.

SCM is a well-known discipline that manages the physical flows and information services from the product's origin to the product's consumption. The primary goal of SCM is to be efficient and cost-effective across the entire system: from transportation to distribution and inventories of products. This goal makes SCM a strategic issue for any business desiring to meet different goals in terms of economic competitiveness, time, and quality of service.

SCM contains three well-known decision-making levels: strategic, tactical, and operational. In particular, at the strategic level, the main goal is to design the supply chain configuration. Supply Chain Network Design (SCND) includes the decisions concerning the number and location of manufacturing and distribution facilities, the facilities' capacity, the conciliation of market demand, and decisions on supplier selection from a total cost perspective [Chopra and Meindl, 2007]. The location of strategic facilities has a major impact on the company's future supply chain, and the way of financing large investments over a long term horizon directly impacts the company's financial situation and future value. However, financial considerations are generally omitted in most SCND mathematical models. This thesis contributes to fill the gap between the scientific domains of management science and finance.

FILEAS FOG research project

The thesis has been done within the context of the FILEAS FOG project, funded by Agence Nationale de la Recherche (ANR), under the ANR 17-CE10-0001-01 grant.

The main goal of the FILEAS-FOG project is to explore ways to improve the compet-

itiveness of supply chains thanks to a better integration of logistic and financial decisions. This implies a decompartmentalization between supply chain and financial decisions.

This collaborative research project is carried out by two complementary research teams on a triptych finance-logistics-operations research. This project is multidisciplinary in nature as it is at the border between corporate finance, supply chain management, and operational research. Most of the participants are involved in logistics issues, which will therefore be approached through the dual prism of management and operations research.

The project addresses both the strategic and tactical decision levels, but this thesis focuses on the integration of strategic logistic and financial decisions (facility location and long-term investments). This thesis represents one work package of the FILEAS FOG project, focusing on the strategic decision level.

Facility location problems and supply chain network design

In operations research, location problems are understood as the determination of the best location(s) to set facilities while minimizing some logistic costs (set-up, industrial operations, transportation, etc.).

The story of facility location problems, summarized in Marianov and Serra [2011], takes its source in the first half of the 17th century, with the independent works of Cavalieri, Fermat and Torricelli. Their application to industrial problems was first mentioned by Weber and Peik [1909], in the context of a continuous problem for locating a single factory. The real development of modern discrete location models started in the early 1960s, with the formulation of the p-median problem and the contemporary works of Manne, Balinsky, Kuehn, and Hamburger. The first paper with an integer programming formulation of the p-median problem was proposed by ReVelle and Swain [1970].

In the last twenty years, we have seen the emergence of increasingly rich models, i.e., integrating a large number of realistic features, constituting the main facets of SCND-related researches:

- the presence of several echelons in the logistic chain, for example, suppliers, factories, warehouses, customers,

- the consideration of several products, possibly linked by a bill of materials,

- complex flows of products between the different units, in particular direct deliveries to certain customers from factories, and reverse flows,
- choice between several levels of technology, several transportation modes,
- hybridization of strategic and tactical decisions (e.g., inventory management),
- increasingly realistic cost modeling,
- integration of environmental factors.

As suggested by the preceding enumeration, there are many variants of SCND problems. According to these variants, the decision variables can concern the number, the location, and capacity of sites, the flow of materials produced, transformed, stored, and transported in the network. In logistics applications, almost all models concern discrete locations, with a key decision variable associated with each candidate location. This variable takes a value of 1 when the candidate site is selected and 0 otherwise.

Location and SCND problems have given rise to several state of the art papers, that are either very generic or focus on one feature or application of the problem: Beamon [1998], Owen and Daskin [1998], Daskin et al. [2005], Meixell and Gargeya [2005], Sahin and Süral [2007], Melo et al. [2009a], Eskandarpour et al. [2015], Alumur et al. [2015], Ahmadi-Javid et al. [2017], and Laporte et al. [2019]. We can also quote the state of the art of Akçalı et al. [2009], Aras et al. [2010]. for reverse logistics models or models describing closed-loop logistics networks.

When there is only one site to locate among n candidate sites, facility location amounts to simply compare n independent scenarios. When there are several sites to locate, additional constraints and features that enrich the model, the problem becomes difficult both in theory and practice. In the literature, mixed-integer linear programming (MILP) solvers are able to solve medium-sized SCND instances. This is why facility location problems constitute an excellent "playground" to evaluate the performance of heuristics and to test their scaling up potential.

Facility location and finance

Location decisions have long-term consequences on the firm's operations and strong impact on the firm's finance. However, we observe that most mathematical location models

are mainly built on logistic data (transport, stocks, production capacity, lead times, service quality, etc.), and also environmental data. The way logistic decisions are financed and *a fortiori* their long-term financial implications are almost always ignored. In most of the works that mention the integration of financial aspects in location models, the financial issue appears through budget constraints (see Melo et al. [2009b]), calculations of exposure to financial risk (bankruptcy) or logistic risk (stock shortage, delay) (Guillén-Gosálbez et al. [2007], Nickel et al. [2012] and Longinidis et al. [2015].

Very few works explicitly consider objectives or constraints emanating from the world of finance, while financial theory questions the relationship between the value of the firm (linked to its economic activity) and the choice of its financing. This question was initiated by the two founding theorems of Modigliani & Miller. Thus, in line with the objectives of the ANR FILEAS-FOG project, this thesis focuses on the consideration of the issue of financing in a firm's multisite location strategy.

Objectives of the thesis

The main objective is to revisit SCND models by including a financial counterpart to the logistic decision features. The initial challenge was to identify relevant financial tools and indicators to be integrated into SCND-type models.

Then, a modeling work allows expressing these problems in the form of mathematical programs. As the field of SCND includes a large variety of problem variants, we will restrict our study to one relevant mathematical model that can be easily adapted later. In order to focus on the relationship between logistics and finance, we will deliberately consider a simple logistics network with a single product, deterministic demand, and single-objective. This work is intended to be progressively extended in order to incorporate more realistic features and complex supply chains.

As far as the solution methods are concerned, the thesis addresses both the use of a state-of-the-art linear programming solver and efficient metaheuristics able to solve large instances in an acceptable computing time.

Outline of the thesis

This manuscript is organized in six chapters.

Chapter 1 briefly reviews the SCND problem variants by describing the main features

of facility location models, the main solution methods incorporated in the literature, and different potential ways to introduce financial dimensions into the SCND models. Given the number of related bibliographical references, this chapter does not pretend to be exhaustive.

Chapter 2 attempts to identify a suitable financial indicator to be used in SCND models. We review the main financial indicators that can be implemented within an SCND mathematical model.

Chapter 3 presents an extensive mathematical formulation model of an SCND problem incorporating financial decisions, using the indicator identified in Chapter 2.

Chapter 4 is dedicated to the numerical experiments on the model presented in Chapter 3. Two solution approaches are introduced, which aim at representing how integrating financial decisions into SCND models alters logistic decisions. This chapter introduces 60 new data set that are randomly generated. All computational experiments are performed with the IBM Cplex solver.

Chapter 5 describes a Large neighborhood Search (LNS) metaheuristic proposed for solving the single-objective SCND model of Chapter 3. After detailing the solution method, we present numerical experiments validating the performance of the algorithm.

Chapter 6 extends the work by addressing a bi-objective optimization problem. To this end, the logistic and financial decisions are tested against each other as two conflicting objectives. An $\epsilon-$constraint method is first employed to exactly solve the model. Then we propose aMulti-Directional Local Search (MDLS) method that embeds the single-objective LNS presented in Chapter 5.

The manuscript is concluded by an overview of its contributions and a proposal for future research directions.

Chapter 1

Supply Chain Network Design

Supply Chain Management (SCM) was introduced in the early 1980s to help companies to better manage their supply chains by facilitating relationships between internal departments and external trading partners [Mentzer et al., 2001]. SCM development improved management of a company's sourcing, procurement, and logistics activities to satisfy consumer demand, enhance efficiency, reduce inventory, and improve forecasting. Due to the complexity of managing the large-sized physical flows in a supply chain, SCM is traditionally divided into three different decision levels: strategic, tactical, and operational [Anthony, 1965]. These levels differ on the type of decisions and the period of time over which decisions are made.

The strategic decision level: This level is also known as supply chain design, that typically considers long-term decisions related to the definition of the main goals and resources of the company: definition of products and markets, facility location, sourcing, determining production capacity and transportation modes, technological choices for the infrastructure, and the information system that supports supply chain operations. The time horizon of strategic decisions covers several years. Depending on the field of application it much shorter in food industry or technological consumer products than in pharmaceutical or aeronautical industry.

Tactical decision level: This level is also known as supply chain planning, that plans the utilization of the company's resources over a medium-term horizon. Typical decisions are related to production planning (sales and operations planning, master production schedule), inventory management, purchasing and supply, pricing discount planning, choice of carriers or types of vehicles.

Operational decision level: This level, also known as supply chain operations, concerns short-term decisions, from a few minutes to a few days. Typical decisions are related

to production scheduling and monitoring, inventory control, sales support, vehicle routing.

Supply chain design, planning, and operations significantly impact a supply chain's future achievement and profitability. In particular strategic decisions that determine a supply chain's physical structure notably impact its performance [max Shen, 2007]. It also has major consequences on the future tactical and operational decisions [Farahani et al., 2014]. Determining the physical structure of a supply chain is called Supply Chain Network Design (SNCD). Traditionally, SCND aims at optimizing strategic decisions such as "where" and "when" to locate facilities, how to set the capacity of facilities and how to optimally connect all facilities of a given logistics network. It has been the subject of a vast literature and many reviews (see, e.g. Melo et al. [2009b] and Alumur et al. [2015]). Most of this literature identifies the facility location problem and its extensions as the core of SCND models. Hence, we briefly recall the facility location models in the following section.

1.1 Facility location models

Facility location models, in a basic formulation, includes a list of candidate locations to install the facilities, and a list of demand points that must be serviced. The primary goals of these models are (i) to define the network itself by selecting locations for the main logistics facilities and defining the allocation of product flows to these facilities, (ii) to determine the optimal product flows in these logistics networks. Different types of these models exist in the location science literature:

***p*-median models** The p-median problem (investigated by [Hakimi, 1964, 1965]) is one of the basic facility location models in which there are a finite set of candidate locations. The goal is to select p locations, also known as medians, among the candidates such that the cost of satisfying the demand is minimized.

***p*-Center Models** The p-center problem is later investigated by [Hakimi, 1964]. This model aims to locate p centers so that the maximum distance between the demand nodes and that center is minimized (hereby, this is also called the mini-max problem).

Fixed-charge facility location models The fixed-charge facility location problem seeks to establish some facilities among a finite set of candidates, minimizing both costs

of establishment and cost of serving the demand points.

Covering location models The covering location problem addresses the issue of covering a prescribed distance between the demand points and the located facility. Generally, there are two types of covering location problems: the set covering problem and the maximal covering problem. The former (introduced by [Toregas et al., 1971]) aims to minimize the total cost of setting facilities to cover all the demand points. The latter (introduced by [Church and Velle, 1974]) deals with installing the facilities such that the number of covered demand points is maximized.

1.2 Features of SCND models

Facility location models can be categorized according to their different features. Here we shortly discuss some of the main features of these models. They are listed according to the chapter names of the book *Location Science* [Laporte et al., 2019].

Capacitated vs. un-capacitated Uncapacitated SCND models assume that the facilities' capacity is infinite. In this case, there is no restriction on the demand allocation. On the other hand, i.e., the capacitated facility location models, capacity is limited, and the demand should be allocated carefully not to violate the facility's capacity.

Deterministic vs stochastic In real-world problems, models inputs are usually not known with certainty. Forecasted data are uncertain by nature and parameters such as costs, productivity, and capacity are subject to variations. The models that ignore the uncertainty and deal with certain inputs are called deterministic; those considering the effect of uncertain inputs are called stochastic.

Single-period vs. multi-period Being static (=single-period) or dynamic (=multi-period) is among the main features of facility location models. Facility location decisions are generally valid on a long term horizon. Installed facilities shall be used for a certain number of years. Moreover, these decisions are expensive to modify on a short-term basis.

Single-period facility location models are designed to make robust decisions for one representative period, which is adequate for future use. Multi-period models are designed to cope with different parameters, which may change over time within a given planning horizon, but predictably [Melo et al., 2009b].

Single-product vs. multi-product Facility location models can concern single-product or multi-products. Single-product models assume that different parameters such as demand, capacity, and cost of several products can be aggregated into one selected type of product. Multi-product models handle several products simultaneously, focusing on differences in raw materials, capacities used, costs, and sales individually for each product type.

Single-echelon vs. multi-echelon The single-echelon supply chain considers the product flows associated with only one stage between the upper and the lower level, e.g., between manufacturing sites and clients. In a multi-echelon supply chain, the product flows traverse several layers, e.g., from suppliers to manufacturing centers, then from manufacturing centers to distribution centers, and from distribution centers to customers

1.3 Solution approaches for SCND

Generally, combinatorial optimization problems, including SCND, can be solved using two main types of approaches. Exact algorithms result in an optimal solution in bounded but potentially very large time. This category also contains the use of MILP solvers, which can be very efficient as long as the size of instances is not too large. Heuristics and metaheuristics are approximate algorithms able to find non-optimal (hopefully good) solutions in very limited time. Thus, they are mainly used to solve larger instances of complex problems.

The goal of this section is to review the dedicated solution methods used to solve SCND problems. This section is divided into two subsections. Subsection 1.3.1 deals with methods employed to solve single-objective mathematical models. Subsection 1.3.2 reviews the methods used to solve multi-objective mathematical models.

1.3.1 Solution methods for single-objective models

A large variety of exact, heuristic, and metaheuristic techniques have been applied to solve SCND problems. Table 1.1 lists some of the main methods, and for each of them refers to a restricted list of bibliographical references. Note that this table is far from being exhaustive. The references have been selected on the basis of a personal choice. In this section we discuss some of these methods.

Type of Method		Selected publications
Exact	Benders' decomposition	Santoso et al. [2005], Poojari et al. [2008], Bidhandi and Yusuff [2011], Noyan [2012], Zheng et al. [2019]
	Column Generation	Shen et al. [2003], Shu et al. [2005], Shen [2006], Shu et al. [2010], An and Wilhelm [2014], Zhong et al. [2018], Li et al. [2021]
Heuristic	LP-rounding	Cordeau et al. [2006b], Thanh et al. [2010], Melo et al. [2012], Albareda-Sambola et al. [2013], Melo et al. [2014], Fattahi et al. [2015], da Silveira Farias et al. [2017]
	Lagrangian Relaxation	Daskin et al. [2002], Shen and Qi [2007], Cui et al. [2010], Snyder et al. [2007], Hammami et al. [2009], Marufuzzaman et al. [2014], Khatami et al. [2015], Keyvanshokooh et al. [2016], Kheirabadi et al. [2019]
	Primal-Dual	Erlenkotter [1978], Dias et al. [2007], Marques and Dias [2013]
Single solution metaheuristics	SA	Jayaraman and Ross [2003], Subramanian et al. [2013]
	TS	Lee and Dong [2008], Melo et al. [2012]
	LNS	Pereira et al. [2015], de Sá et al. [2015], Eskandarpour et al. [2017], Souto et al. [2021]
Population-based metaheuristics	GA	Altiparmak et al. [2009], Wang and Hsu [2010], Hiassat et al. [2017]
	PSO	Kadadevaramath et al. [2012], Mogale et al. [2020]
	MA	Fahimnia et al. [2013], Nasiri et al. [2021]

Table 1.1 – Solution Methods for single-objective SCND models

1.3.1.1 Exact methods

Benders' decomposition Benders decomposition algorithm (proposed by Benders [1962]) is one of the most widely implemented techniques in decomposing mathematical models that include some *complicating variables*. Temporarily fixing the value of the complicating variables yields sub-problems that are significantly easier to handle. This technique consists of a sequence of projection, outer linearization, and relaxation (Geoffrion [1970a,b]). The primary problem is decomposed into a master and a sub-problem. The approach then generates a set of cuts by iterating between the master and the sub-problem. The master problem includes the integer variables and the generated cuts, while the sub-problem includes the continuous and integer variables as parameters.

This method has been applied successfully in the SCND problems. For instance, Santoso et al. [2005] develop a stochastic SCND problem that aims at minimizing the investment and operational costs. They propose an accelerated Benders' decomposition to solve realistic scale instances. More recently, Zheng et al. [2019] address a joint inventory-routing-SCND model. The model, which minimizes the total logistic costs, includes some non-linear expressions. Applying Benders' decomposition method, the model is decomposed by including the non-linear terms into the sub-problems. Table 1.1 reports some other relevant studies.

Column generation Column Generation is a tool in computational optimization used to solve large-scale mathematical models. As large-scale mathematical models often include an exponential number of variables, this technique is employed to consider a restricted number of variables (also called columns). Hence, the whole set of variables is not explicitly considered. This is done by decomposing a given problem into a master and a sub-problems. The optimal solution of the master problem is either proved optimal (which ends the algorithms) or the best possible new column is appended to the current model by solving the new problem.

Some of the papers using the column generation in SCND models are reported in Table 1.1. For instance, Shen [2006] propose an SCND model with the goal of profit maximization, where column generation is used to solve their relaxed linear programming model. Li et al. [2021] study a warehouse–retailer SCND problem minimizing the total costs. Since the model includes an exponential number of variables, a column generation algorithm is employed to solve the linear relaxation of the proposed model.

1.3.1.2 Heuristic methods

LP-rounding LP-rounding method is based on solving a linear-relaxed version of an integer program (replacing all integrality constraints by their continuous counterpart) and then converting the resulted fractional solution into a feasible integer solution. Solving the relaxed version provides a lower/upper bound for the minimization/maximization problems, which is not always feasible. Despite that, the relaxed model can be easily solved with solvers and provide reasonable bounds for the integer model.

Thanh et al. [2010] study a multi-period, multi-echelon, multi-commodity SCND problem. An LP-rounding method followed by a repair procedure is employed to solve the proposed model. The solution method is tested by solving small, medium, and large-sized instances. The average reduction of computational time is 80% for the small and medium-sized instances and at most 51% for large-sized instances.

da Silveira Farias et al. [2017] develop a heuristic approach combining an LP-rounding, and a multi-start mechanism to solve a strategic SCND model. The LP-rounding algorithm is used to find the initial solution and solve the generated models by the multi-start mechanism. The solution method is evaluated by solving a set of randomly generated instances. The numerical experiments indicate an average gap of 2.50%, which is reported as competitive compared to previous studies.

Lagrangian relaxation Lagrangian Relaxation (LR) is based upon the observation that many complex integer programming problems can be modeled as a relatively easy problem complicated by a set of side constraints [Fisher, 1985]. This method consists of finding relaxed bounds for the combinatorial optimization problem (i.e., upper bounds for maximization problems and lower bounds for minimization problems). LR decomposes the primal problem into smaller sub-problems and then solves each sub-problem almost independently.

There are several references using the LR method in SCND models. For example, Hammami et al. [2009] present a global tactical-strategic SCND model to maximize the global profit after tax of the company. The model is evaluated by optimally solving small and medium-sized instances using the Cplex solver. However, to solve larger-sized instances, they propose an LR-based solution method enabling them to solve those instances in a reasonable time. Another example is the work of Kheirabadi et al. [2019] who develop an MILP model and propose an LR-based solution method. Their numerical experiments denote the efficiency of the developed LR in solving large-sized instances. Without LR,

Cplex could solve only 42% of large instances with an average gap of around 65%, whereas applying LR enables them to solve all the large instances with an average gap of less than 2%.

Primal-dual The primal-dual algorithm is a heuristic solution method to solve combinatorial optimization problems. This method is an iterative-based algorithm that constructs feasible primal and dual solutions in each iteration. The algorithm starts with a dual solution and uses dual information to infer a primal solution.

The work of Dias et al. [2007] is one of the examples that use the primal-dual heuristic method for a dynamic location problem. The presented problem is NP-hard; thus, the authors developed a primal-dual heuristic solution method to solve the model. Additionally, A branch and bound algorithm is developed to guarantee the calculation of the optimum solution whenever the heuristic algorithm is unable to find it. The computational experiments indicate the efficiency of the primal-dual heuristic in finding good-quality solutions.

1.3.1.3 Meta-heuristic methods

In the SCND literature, almost all well-known metaheuristics have been implemented. These methods can be classified according to the number of solutions used simultaneously: single-solution methods and population-based methods. The former attempts to generate an initial solution that is gradually improved during the search process, such as Simulated Annealing (SA), Tabu Search (TS), and Large Neighborhood Search (LNS). The latter works with multiple solutions in a parallel manner, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Memetic Algorithm (MA).

For instance, Melo et al. [2012] develop a TS solution method for solving a supply chain network redesigning problem. A set of randomly generated instances is used to evaluate the quality of the solutions obtained by the TS algorithm. Also, a comparison between TS, Cplex, and an LP-rounding solution method is drawn. This comparison denotes the efficiency of TS in finding good quality solutions (the average gap of 1% to the LP-rounding solutions) in an acceptable CPU time.

A recent example is the work of Mogale et al. [2020] that study a wheat SCND problem minimizing the total supply chain cost. They develop a PSO as well as an extended PSO called GLNPSO to solve the proposed model. The results obtained by the solution methods are compared with the Cplex solutions indicating the outperformance of GLNPSO.

1.3.2 Solution methods for multi-objective models

Many classical multi-objective optimization approaches help decision-makers find trade-off solutions and select the best one. Here we mention some of the main methods implemented in the literature. Table 1.2 lists a selection of relevant references for each method.

1.3.3 Exact methods

Weighted sum of objectives Giving weight to each objective function and optimizing the weighted sum of all objectives is a way to handle the multi-objective models. This approach transforms multiple objectives into a single one. The resulting model, thus, can be solved using any method for single-objective optimization. Unfortunately, this method may not describe the decision maker's interest and may alter the Pareto structure of the problem[Pozo et al., 2012]. It can be used only when the Pareto set is convex.

Melachrinoudis and Min [2000] is among the references using the weighted sum of objectives method. They study a multi-objective mixed-integer SCND model. The model includes three objective functions: maximizing total profit, minimizing total access time, and maximizing aggregated local incentives. The multi-objective model is transformed into a single objective by dedicating equal weights to each objective function.

Karadağ et al. [2021] is a more recent reference addressing the problem of designing a blood supply chain network. The problem is modeled as a bi-objective optimization aiming to minimize the distances between the blood supply chain elements and the length of the mobile unit routes. Each objective is dedicated with a coefficient, and their weighted sum is minimized.

Epsilon-constraint The ϵ-constraint method (proposed by Haimes [1971]) prioritizes the objectives such that one is set as the primary objective and others as the model's constraints. The value of ϵ is defined as a set of upper bounds of estimated objective function values determined by decision-makers [Cui et al., 2017].

Guillén-Gosálbez et al. [2008] design a sustainable supply chain network considering two conflicting objectives. The first objective is to minimize the total network cost and the second objective is to minimize the environmental impacts. An $\epsilon-$constraint method is employed to solve the model.

Another recent example is the work of Huang et al. [2020] that deals with developing a sustainable multi-objective SCND model based on the waste material recycling and

Type of Method		Selected publications
Exact	Weighted sum of objectives	Caruso et al. [1993], Melachrinoudis and Min [2000], Krikke et al. [2003], Melachrinoudis et al. [2005], Galante et al. [2010], Bernardi et al. [2013], Cheng et al. [2018], Karadağ et al. [2021]
	$\epsilon-$constraint	Guillén-Gosálbez et al. [2008], Chaabane et al. [2011], You and Wang [2011], You et al. [2012], Amin and Zhang [2013], Mota et al. [2015], Canales-Bustos et al. [2017], Huang et al. [2020]
Multi criteria decision analysis	Goal Programming	Galante et al. [2010], Chaabane et al. [2011], Gholami et al. [2019]
	Fuzzy approach	Malczewski and Ogryczak [1990], Pinto-Varela et al. [2011], Sharifi et al. [2020]
Single solution metaheuristics	SA	Mohammadi et al. [2014], Chibeles-Martins et al. [2016]
	TS	Caballero et al. [2007], Cardona-Valdés et al. [2014]
	VNS	Eskandarpour et al. [2013, 2014], Devika et al. [2014]
	LNS	Eskandarpour et al. [2021]
Population-based metaheuristics	GA	Altiparmak et al. [2006], Dehghanian and Mansour [2009], Zhang et al. [2013], Ehtesham Rasi and Sohanian [2021]
	MA	Pishvaee et al. [2010], Jamshidi et al. [2012]
	PSO	Ganguly et al. [2011], Shankar et al. [2013b,a], Azadeh et al. [2017]
	Ant Colony	Moncayo-Martínez and Zhang [2011], Zohal and Soleimani [2016]
	Scatter Search	Du and Evans [2008], Olivares-Benitez et al. [2013]
	NSGA-II	Saffar et al. [2014, 2015], Zhao et al. [2016], Kadziński et al. [2017], Kumar et al. [2017], Azadeh et al. [2017]

Table 1.2 – Solution methods for multi-objective SCND models

exchanging network. Three pillars of sustainability, namely economy, environment, and society, are considered as the objective functions. An $\epsilon-$constraint method is used for each pair of objective functions to solve the proposed model and provide a Pareto frontier.

1.3.3.1 Multi-criteria decision analysis and interactive methods

Multiple-Criteria Decision Analysis (MCDA) is another technique that is able to cope with a large number of objectives and criteria.

There are different techniques associated with the MCDA approach. So far, some of these techniques have been employed in SCND literature, such as goal programming. Goal programming (proposed by Charnes and Cooper [1977]) is a method typically employed when satisfying some of the model's constraints is not possible. This method aims to minimize deviations of the objective function from a specified goal.

Interactive methods are typically preferred when the number of criteria increases and when the decision-makers wish to be involved in constructing a solution. Among the methods, Interactive fuzzy approach is one of the implemented approach in the literature of SCND.

For instance, Galante et al. [2010] address a location problem in the context of solid waste management. A multi-objective framework is used to model the problem, in which minimization of total costs and minimization of environmental impacts are identified as two conflicting objectives. Three different methods, i.e., goal programming, weighted sum, and fuzzy multi-objective, are employed to solve the proposed model. Finally, the authors discuss the difference between the mentioned approaches and point out the decision-makers preferences in using each method.

1.3.3.2 Metaheuristics

There are different types of metaheuristic techniques used for multi-objective SCND problems. Similar to the single-objective techniques, they can be classified into single-solution and population-based solution algorithms.

Simulated Annealing (SA), Tabu Search (TS), Variable Neighborhood Search (VNS), and Large Neighborhood Search (LNS) are among the main single-solution techniques, and Genetic Algorithm (GA), Memetic Algorithm (MA), Particle Swarm Optimization (PSO), Ant Colony, Scatter Search, and Non-dominated Sorting GA (NSGA-II) are among the main population-based techniques used to solve multi-objective SCND problems.

Eskandarpour et al. [2021] present an Multi-Directional Local Search (MDLS) to solve a bi-objective sustainable SCND that minimizes logistic costs and CO_2 emissions. The MDLS method embeds an LNS algorithm to solve the single-objective problems. The MDLS is favorably benchmarked against an $\epsilon-$constraint method, both in terms of computational time and quality of the solutions, particularly for the large-sized instances.

Kumar et al. [2017] propose an NSGA-II algorithm for an SCND model with three objectives: maximizing total profit, minimizing supply disruption and opportunism risks, and minimizing carbon emissions. Each pair of objectives is tested against each other, resulting in different Pareto sets.

1.4 Financial dimension in supply chain network design

Classically, supply chain networks are designed according to economic criteria such as cost minimization or profit maximization. Performance-based criteria such as service level or responsiveness maximization are also among the traditional objective functions adopted in the SCND models. Nowadays, other criteria including sustainability, energy, and financial factors, are employed in network design. The importance of incorporating financial considerations into SCM has been reported many times in the literature. [Applequist et al., 2000, Shapiro, 2004, Shah, 2005, Hammami et al., 2009, Papageorgiou, 2009, Melo et al., 2009b, Longinidis and Georgiadis, 2011]. For instance, Shapiro [2004] discusses the links between supply chain, demand, and corporate financial decisions at the strategic level. He mentions the strong interaction between the financial factors and the strategic planning of firms and organizations. Similarly, Melo et al. [2009b] mention the strong influences of financial factors on the network configuration.

Regarding the significant importance of financial decisions, the primary goal of this thesis is to integrate financial decisions into the process of SCND, which can be done in different ways. First, when dealing with supply chain and finance, the well-known concept of Supply Chain Finance (SCF) immediately comes to mind. However, it is not exactly the topic of this thesis, as explained in Section 1.4.1. Section 1.4.2 lists financial tools and metrics that are often incorporated in the model constraints. Section 1.4.3 lists the financial metrics that are incorporated into SCND objective functions.

1.4.1 Supply chain finance

Supply Chain Finance (SCF) studies the intertwinement of financial and operational decisions [Wuttke et al., 2016]. It mainly aims at optimizing the financial flows within the entire supply chain network [Hofmann, 2005] through solutions implemented by financial institutions [Camerinelli, 2009] or technology providers [Lamoureux and Evans, 2011]. According to Steeman [2014], Liebl et al. [2016], Templar et al. [2020], SCF can be seen from three different perspectives (see Figure 1.1).

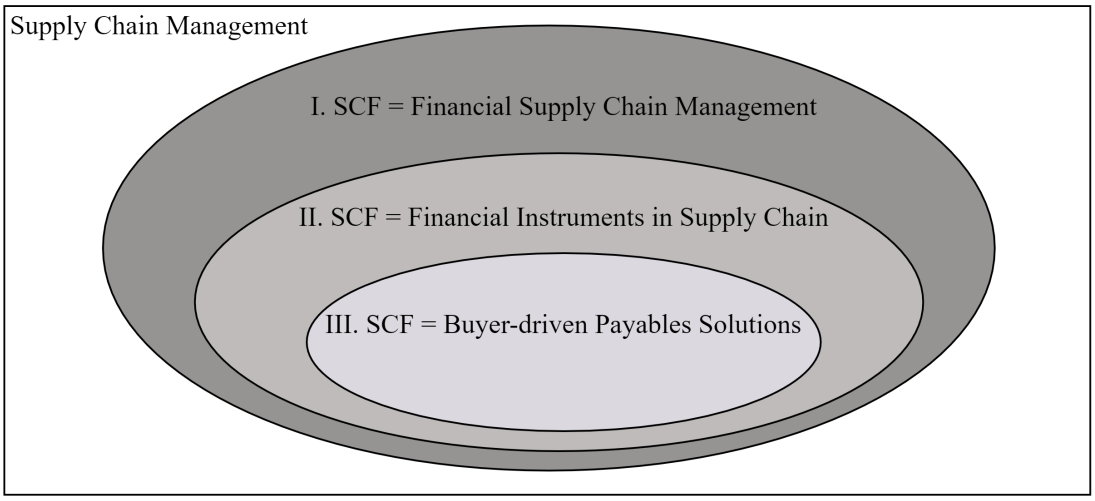

Figure 1.1 – Perspectives to SCF [Zhao and Huchzermeier, 2018]

First, it refers to the management of the financial flows of a supply chain network. Related to this perspective, which takes a rather broad stand, Wuttke et al. [2013a] define SCF as "optimized planning, managing, and controlling of supply chain cash flows to facilitate efficient supply chain material flows". Another definition is given by Blackman et al. [2013] as "network of organizations and banks that coordinate the flow of money and financial transactions via financial processes and shared information systems in order to support and enable the flow of goods and services between trading partners in a product supply chain." The similar definition can be found in Pfohl and Gomm [2009], Gomm [2010], Silvestro and Lustrato [2014].

The second definition of SCF is focused on liquidity optimization and enhancing the monetary flows of a supply chain. From this standpoint, SCF determines the financial instrument incorporated to fund the strategic, tactical or operational decisions. These financial instruments then are included into the financial supply chain management.

Camerinelli and Bryant [2014] define it as "the use of financial instruments, practices, and technologies to optimize the management of working capital, liquidity, and risk tied up in supply chain processes for collaborating business partners". It is also defined by Pfohl and Gomm [2009] as "the inter-company optimization of financing as well as the integration of financing processes with customers, suppliers, and service providers in order to increase the value of all participating companies." Similar definitions can be found in Hofmann [2005], Camerinelli [2011], de Meijer and De Bruijn [2014].

Finally, the last perspective describes supplier financing as a buyer-driven payable solution. This perspective which mainly focuses on reverse factoring is defined by Tanrisever et al. [2012] as "in a reversed factoring arrangement, a corporation and its supplier work together with a bank, in order to optimize the financial flows resulting from trade". Another definition is "the lender purchases accounts receivables only from specific informationally transparent, high-quality buyers. The factor only needs to collect credit information and calculate the credit risk for selected buyers, such as large, internationally accredited firms" [Klapper, 2006]. The similar definition can be found in Wuttke et al. [2013b], Dyckman [2009], Moritz et al. [2016].

All in all, SCF is considered to be a lever for optimizing strategic, tactical or operational financial decisions, by coordinating the decisions of the players in a supply chain. This naturally leads to game theory models, whose objective is to find an equilibrium between all actors of a given supply chain. Moreover, the primary benefits of SCF rely on the cooperation of all supply chain participants to enhance the financial flows as well as trust and commitment throughout the chain.

The issues mentioned above are far from the goal of this thesis. Instead, we intend to study strategic supply chain planning by incorporating some financial decisions into the supply chain design stage and not coordinating the decisions of different supply chain players or enhancing their trust and commitment.

1.4.2 Financial tools and metrics in model constraints

In their review on facility location and supply chain management, Melo et al. [2009b] classify financial factors in three categories: (i) *international factors* (including taxes, duties, tariffs, exchange rates, transfer prices, and local content rules), (ii) *financing and taxation incentives* offered by governments and (iii) *investment expenditures*, usually limited by the total available budget. Here we discuss each class by reviewing some of the relevant publications.

(i) International factors In the first category, Vidal and Goetschalckx [2001] formulate a global SCND model to maximize the net income after tax. Different corporate tax rates associated with different countries are considered in their model. Moreover, the model's constraints include the transfer price (for raw materials and finished products), subject to upper and lower bounds. They also develop a heuristic approach called successive LP solution procedure to solve the model. Avittathur et al. [2005] study the effects of different sale taxes on locating the distribution centers. Minimizing the costs including the fixed cost of distribution centers, safety stock inventory cost, transit cost, transportation cost, additional sale tax cost, is set as the objective function. In addition to considering different sale tax rates, the effect of different parameters such as distribution center's fixed cost, service level, transportation cost, and demand distribution is investigated. The General Algebraic Modeling System (GAMS) is used to evaluate an approximated version of the mixed-integer non-linear programming (MINLP) problem. Hammami et al. [2009] propose a global SCND model in a relocation context, with both tactical and strategic decision levels. The goal is to maximize the global profit after tax of the company. The financial decisions are the transfer pricing and two variables allocating supplier costs and transportation costs. For small and medium-size instances, Cplex is used effectively, while as the size of the instances increases, Cplex loses its efficiency. Thus, they propose a Lagrangian Relaxation (LR)-based approach to cope with the large computational times and memory problems for solving large instances. Kristianto and Gunasekaran [2018] investigate the design of a supply chain considering strategic, tactical, and operational decision levels. The objective function of their proposed model is to minimize the total costs at all mentioned decision levels. Various factors such as exchange rates, transfer pricing, taxation, and import duties are involved in the model. The model is formulated as a mixed-integer nonlinear programming (MINLP). A solution approach consisting of a two-stage branch-and-bound algorithm with cutting planes and under-estimators is proposed to solve the model using the BARON solver.

(ii) Financing and taxation incentives In addition to exchange rates, transfer prices, and taxes, Canel and Khumawala [2001] consider the government incentives via taxes and subsidies in a global supply chain design problem. They propose a single-item multi-period international SCND model aiming at maximizing the profit after tax. The model, formulated as a MIP, is solved using an iterative heuristic implemented in the LINDO solver. Referring to the importance of tax incentives in a global SCND problem, Melachrinoudis

et al. [2005] develop a multi-objective multi-criteria mixed-integer linear programming model. The model's first objective is to minimize the total distribution costs comprised of production costs, fixed and variable warehousing costs, warehouse relocation costs, and inbound and outbound distribution costs. The second objective aims at maximizing the customer service level by maximizing the demand coverage. The last objective relates to the intangible benefits that are maximized. To solve the proposed multi-objective model, an aggregated objective function of the criteria is developed, and the resulting model is solved using the LINGO solver.

Recently the financial incentives offered by the government is to encourage the managers to use the cleaner technologies. For instance, Chalmardi and Camacho-Vallejo [2019] propose a bi-level sustainable SCND dealing with the environmental impact caused by plants and distribution centers as well as transportation. Their model includes the effect of financial incentives offered by the government to encourage using cleaner technologies for the plants. They define a leader (an Environmental Protection Agency from the government) who tries first to optimize the environmental aspects. Then a follower (the supply chain's manager) who considers optimizing the economic aspects. In order to solve the proposed bi-level model, a simulated annealing algorithm followed by the Cplex solver is proposed. Their numerical experiments indicate that financial incentives are positively linked to the use of cleaner technologies and reducing environmental impacts.

Esmaeili et al. [2020a] study a problem of designing a sustainable biomass supply chain network under both economic and environmental goals. A mathematical formulation for a second-generation biomass bio-ethanol supply chain is first proposed by the authors. Then, comparing the existing first-generation and the proposed second-generation, authors encourage the supply chain managers to switch their technology. The financial motivations are monetary incentives and penalized carbon emissions considered in the form of the carbon tax. The economic and environmental goals of the work are addressed by maximizing the profit with and without carbon emission penalties. The proposed optimization problem is solved via OpenSolver 2.9.0 using CBC (COIN-OR Branch-and-Cut) optimization engine.

(iii) Investment expenditures Budget constraints can be found in numerous facility location models. For example, Melachrinoudis and Min [2000] develop a multi-objective (maximizing profit, minimizing total access time, and maximizing aggregated local incentives), multi-period relocation problem considering budget constraint for the operation

and maintenance of the facilities. To evaluate the model, first, a single objective model using a weighted sum of the objectives is proposed. Then the resulting model is solved using the LINGO solver. Wang et al. [2003] address a facility location problem considering budget constraints with the aim of minimizing the overall distance traveled. Three heuristic approaches (greedy interchange, tabu search, and Lagrangian Relaxation (LR) approximation) are developed to solve the proposed model. In addition to the heuristics, the optimal solutions are obtained using the Cplex solver. Finally, a comparison between the heuristics and the exact solutions is performed. Similarly, Melo et al. [2006] propose a multi-period mathematical model minimizing total business costs. The available budget limitation is the incorporated financial factor. To evaluate the proposed MIP formulation, a set of instances with a reasonable size is solved using the Cplex solver. Nickel et al. [2012] address a multi-period stochastic SCND problem to maximize the total financial benefit of the firm considering uncertain demands and interest rates, with a budget constraint on investments and the possibility of setting a target for the return on investment. As the model is complex, a simplified version of the model (path-based approach) is proposed. The resulting formulation is solved using the Cplex solver. Concerning the disaster problems, Duhamel et al. [2016] present a multi-period location-allocation model considering the impact of distribution over the population. The model that aims to maximize the total population assisted includes budget restrictions for opening local distribution centers. To solve the model, a decomposition-based heuristic approach is developed. It decomposed the model into a master and a sub-problem. The former corresponds to solving the location problem using the NOMAD solver, while the latter makes the distribution decisions using black-box coupling heuristics and a Variable Neighborhood Descent (VND) local search. More recently Karadağ et al. [2021] present a multi-objective mixed-integer mathematical model to design a four-echelon blood supply chain network. The financial factor of the work is the allocated budget for the opening and operation of the facilities. Using the Analytical Hierarchy Process (AHP), different objective functions (distances between the network elements and the length of the mobile unit routes) are scored and combined as a single objective function. This objective function indirectly minimizes the transport time and cost and maximizes the products' shelf lives. The model is solved with the Gurobi solver.

1.4.3 Financial objectives

The traditional objective functions in the SCND models, i.e., cost minimization or profit maximization does not essentially drive business growth. Business growth, which can be expressed in the form of a firm's value, is the fundamental goal of any business. Subsequently, over recent decades the concept of value-based management, which aims at maximizing the whole firm's value has been used in SCM [Christopher and Ryals, 1999, Shapiro, 2001, Hahn and Kuhn, 2012, Brandenburg, 2013, Badri et al., 2017, Zhang and Lam, 2018, Zhang et al., 2020].

According to the concept of value-based management, the firm's value is determined by its ability to generate future cash flows, which, in turn, is driven by profitability, capital efficiency, and cost of capital [Rappaport and Value, 1998, Seuring et al., 2005, Damodaran, 2010, 2011, Brandenburg, 2013]. The mentioned drivers are all affected by various decisions such as investment, financing, and operations. Hence, developing a value-based supply chain enables managers to have a holistic overview of several decisions.

Value-based management has also been subjected to a few publications developing SCND models: [Laínez et al., 2007, Longinidis and Georgiadis, 2011, 2013, Ramezani et al., 2014, Steinrücke and Albrecht, 2016, Mohammadi et al., 2017, Yousefi and Pishvaee, 2018, Polo et al., 2019, Borges et al., 2019, Vidal-Holguín et al., 2020, Sabogal-De La Pava et al., 2021]. In these publications, value-based management has been modeled using several financial indicators adopted as the objective function of the SCND process. In Chapter 2, we review different methods to firm valuation as well as different financial indicators to identify the most relevant to the goal of this thesis. Thus the mentioned references are discussed in detail in that chapter.

Solution approach		Article
Solver	Cplex	Laínez et al. [2007], Longinidis and Georgiadis [2011] Ramezani et al. [2014], Mohammadi et al. [2017] Yousefi and Pishvaee [2018], Polo et al. [2019]
	Dicopt	Longinidis and Georgiadis [2013]
	Scip	Steinrücke and Albrecht [2016]
	Gurobi	Borges et al. [2019]
Heuristic + solver	Primal + Cplex	Sabogal-De La Pava et al. [2021]

Table 1.3 – Solution Approaches used in the articles dealing with SCND and value-based management

Concerning the solution approaches of these references, only linear programming solvers

are employed to solve their models, or a mix of a heuristic approach and a solver is used. Table 1.3 summarizes the solution approaches of the above references.

1.5 Concluding remarks and research proposal

This chapter reviewed the facility location and supply chain network design literature, focusing on the integration of logistics and finance. We briefly reviewed the main features of SCND models and reviewed different solution approaches implemented to solve single-objective and multi-objective SCND models. Table 1.4 summarizes all the properties described in this chapter. It also establishes a research proposal by selecting the main characteristics of the models and solution methods that will be detailed in the next chapters.

			This Thesis
Supply chain network features	Capacitated	vs. un-capacitated	☑☐
	Deterministic	vs. stochastic	☑☐
	Single period	vs. multi period	☐☑
	Single product	vs. multi product	☑☐
	Single echelon	vs. multi echelon	☑☐
	Single objective	vs. multi objective	☑☑
Ways to incorporate financial decisions	Supply chain finance		☐
	Financial constraints		☐
	Financial objective		☑
Solution approaches	Single objective	Modeling tools and solvers	☑
		Benders' decomposition	☐
		Column generation	☐
		LP-rounding	☐
		Lagrangian relaxation	☐
		Metaheuristic	☑
	Multi objective	Weighted sum of objectives	☐
		Epsilon-constraint	☑
		Goal programming	☐
		Fuzzy approach	☐
		Metaheuristic	☑

Table 1.4 – Research proposal

Regarding the supply chain features, there exist many potential variants of models to be studied. We chose to develop a capacitated model since it is more realistic from an industrial point of view. Stochastic models would also be more realistic from a financial

perspective, but as a first step toward the integration of supply chain and finance, we chose to restrict the study to deterministic models. The extension to stochastic models is a natural extension of this work. By nature, financial planning is relevant only in a long-term working horizon. The choice of multi-periodic models was then obvious. In order to keep the model as simple as possible and to focus on the interactions between supply chain and finance, we wanted to keep the logistic part of the model as concise as possible. This justifies the choice of a single product and a single layer of facilities to be located. We study both a single-objective model (Chapter 3) and its extension to a bi-objective model (Chapter 6).

It is striking that financial considerations are frequently considered in the SNCD literature as side constraints but often are not a full component of the decision model. One of the primary purposes of this thesis is to work on mathematical models that consider financial and logistic decisions as two essential parts of the same decision process, according to the concept of value-based management. This is why we chose to include the financial dimension in the objective function. The determination of the appropriate financial indicators that can achieve this goal is investigated in Chapter 2.

Regarding the solution methods, linear programming solvers are powerful enough to solve the basic models and small-sized instances of extended models, such as those integrating sustainable and environmental or financial dimensions. For larger instances, these solvers often lose their efficiency. Therefore, developing efficient specific exact methods or (meta)heuristics is necessary. Chapter 4 of this thesis presents computational experiments led with Cplex and shows the limits of the use of solvers for our proposed model.

Although several publications propose metaheuristics as an efficient solution approach for solving the SCND problems, surprisingly enough, there is no publication using such techniques to solve value-based financial SCND models. Therefore, this thesis also aims to fill this gap by developing a metaheuristic algorithm as a solution approach to solve practical instances for the proposed model. This goal can be achieved by implementing any metaheuristic. Among all possible techniques, the LNS has proven its efficiency and adaptability in addressing problems in the field of logistics/supply chain optimization. In the area of SCND, this method has been proposed by Pereira et al. [2015], de Sá et al. [2015], Eskandarpour et al. [2017], and Souto et al. [2021]. For instance, the work of Eskandarpour et al. [2017] involves designing a four-echelon, single-period, and multi-product sustainable supply chain network. Testing the proposed LNS using a variety of instances and drawing a comparison between Cplex and LNS reveals the reliable and

convincing performance of LNS, particularly for instances of realistic and practical size (through the stability and efficiency of the algorithm in terms of both the quality of the solution and the computation time).

Moreover, the adaptability and flexibility of LNS in defining operators make this technique suitable for several variants of SCND problems. Therefore, we believe this could be a proper technique for our goal. Hence, we chose the LNS framework presented in Chapter 5 for solving our proposed financial SCND model.

We also extend the single-objective model to a bi-objective model to analyze the trade-off between the logistic and financial impact of facility location decisions. Solving such model requires developing a bi-objective solution method that can be compared with solutions obtained by an exact approach (ε-constraint method). We embed the single-objective LNS algorithm into a Multi-Directional Local Search (MDLS) algorithm presented in Chapter 6.

Chapter 2

Identifying A Suitable Financial Indicator

2.1 Introduction

This chapter aims to identify the most appropriate path to design a supply chain network according to the value-based management approach.

First, some accounting and financial definitions are given in Section 2.2. Then Section 2.3 explains the principal financial decisions related to the value-based management. Section 2.4 details the main valuation approaches alongside reviewing the SCND articles using each valuation approach. Following that, Section 2.5 concludes the chapter by determining the best potential choice for the needs of this thesis through drawing a comparison between the presented potential indicators.

2.2 Definitions

We start this chapter by recalling some definitions in accounting and finance, since these concepts are not always familiar to most readers in the field of industrial engineering and operations research.

- **Assets**: everything a company owns which includes tangible items such as buildings, machinery and equipment as well as intangible items such as accounts receivable, interest owed, patents, or intellectual property.
- **Liabilities**: everything a business owes, now and in the future such as bank debts, accounts payable, wages owed, taxes owed.
- **Debt financing** (D): one of the main options of raising the capital for the company's needs. This type of financing involves borrowing money from banks and

financial institutions subject to paying it back with interest.

- **Equity financing** (E): another option of raising capital that involves selling a portion of the company's shares to some investors. The investors then share the future profits of the company.
- **Capital structure**: particular blend of liabilities, mix of debt and equity financing used to finance the company's assets and operations (Figure 2.1).

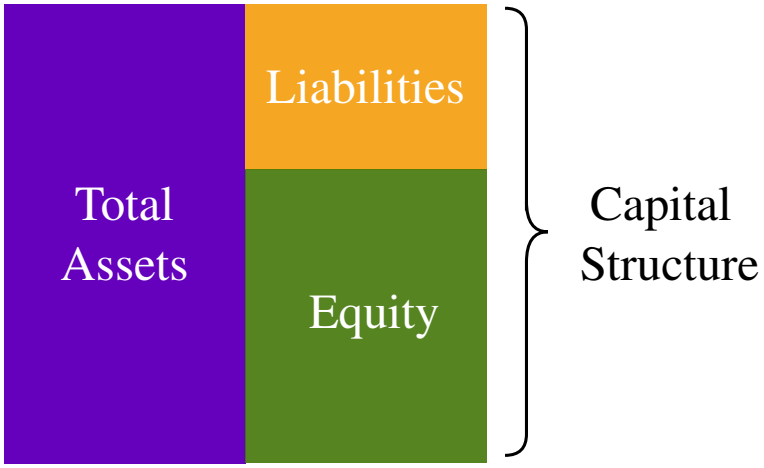

Figure 2.1 – A company's capital structure

- **Cost of debt** (K_D): the return that a company provides to its debt-holders and creditors.
- **Cost of equity** (K_E): the return that the company's shareholders expect for the risk they undertake by investing in that company.
- **Weighted Average Cost of Capital** ($WACC$): the company's cost of capital, obtained by weighting the cost of debt and equity proportionally to their percentage of the total capital structure.
- **Unlevered firm value** (V_U): value of a firm if its capital structure contains only the equity. In other words, there is no debt in its capital structure.
- **Levered firm value** (V_L): value of the firm if it contains debt in the capital structure.

- **Leverage ratio** ($\frac{D}{D+E}$): also known as the debt ratio, is the proportion of debt compared to the total assets of a company. This ratio is a measure that allows for the assessment of companies' exposure to the risk of excessive leverage.

- **Operating profit/cash flows**: the amount of money earned/generated through a company's daily businesses.

- **Non-operating profit/cash flows**: the amount of money earned/generated through a firm's investing or financing activities.

- **Net Operating Profit After Tax (NOPAT)**: a company's after-tax operating profit for all investors, including shareholders and debt-holders.

- **Cash Flow**: the actual movement of cash in and out of a company. Cash flow in (or positive cash flow) is cash received and cash flow out (negative cash flow) is cash paid out.

- **Free Cash Flows** (FCF): measure of the firm's ability to generate cash. In other words, FCF is defined as the difference between both operating and non-operating cash inflows and outflows.

- **Tax Shield Benefit** (TSB): related to the corporate income tax system. Its value is proportional to the corporate tax rate (γ) as well as the interest paid at each period (I_t). Thus its value for period t equals $\gamma \times I_t$. The total value of TSB is calculated as the present value of these interest tax shields.

- **Expected Bankruptcy Cost** (EBC): the estimation of the financial impact of a bankruptcy. This cost is incurred by shareholders. It is calculated as the present value of direct and indirect costs, arising from the firm's inability to service its debt. There are different ways to calculate the expected bankruptcy cost and predict the probability of going bankrupt. Its calculation will be detailed in Chapter 3.

- **Present Value**: also know as discounted value, is the today's value of a future cash flow.

- **Net Present Value (NPV)**: the value of a project's future cash flows, translated into today's money, i.e., the difference between a project's value and its costs *(cash inflows and outflows)* over time. NPV can be either positive or negative.

2.3 Integrating financial decisions through value-based management approach

Value-based management focuses on the fluctuations of the company's value, resulting from both operations and financial decisions. In the industrial engineering literature, supply chains are generally designed based on costs, sales, and revenues (operations decisions). According to this assumption, other value drivers, i.e., capital efficiency and cost of capital (financial decisions), are often ignored. While in value-based management, determining the capital structure plays a role in addition to profitability. Section 2.3.1 discusses how decisions related to the company's capital structure are essential in valuation.

2.3.1 Link between company's value and capital structure

The seminal work of Modigliani and Miller [Modigliani and Miller, 1958] which is known as a milestone in modern finance theory, is the first attempt to explain the relationship between company's value and its financial structure. Modigliani and Miller proposed two complementary theorems. The first theorem concerns a perfect market in which there is no tax [Modigliani and Miller, 1958], and the second theorem captures an imperfect market with tax expense [Modigliani and Miller, 1963].

Theorem 1 (Modigliani-Miller's first theorem)**.** *In competitive, transaction costless, information efficient markets, with no taxes, the market value of the firm (i.e., market value of all of its securities) is independent of the firm' s capital structure.*

Theorem 2 (Modigliani-Miller's second theorem)**.** *In competitive, transaction costless, information efficient markets, with corporate tax-deductibility of interest, the market value of the firm (i.e., market value of all of its securities) equals:*

$$V_L = V_U + \gamma D,$$

where V_L is the value of the firm if it has debt, V_U is the value of the firm if it has no debt, γ is the corporate tax savings per dollar of debt, and D is the market value of the firm's debt.

The Modigliani-Miller second theorem emphasizes the importance of tax-deductibility of debts known as Tax Shield Benefit (TSB) in firm valuation. However, their model has a strong assumption about the risk of debt financing. They ignore distress by allowing

the firm to issue risk-free debt. This is while debt financing is risky inherently. As TSB is recognized as the bright side of using debt, the risk of default or bankruptcy is recognized as its dark side.

Bankruptcy occurs when a firm is unable to repay debts. The bankruptcy cost is composed of both direct components (legal and accounting costs) and indirect components. Indirect costs constitute a continuum of costs that increase at an accelerating rate as exposure to bankruptcy increases, e.g., increased interest expenses, lost credit, lost sales, inefficient operations. Direct costs take the form of administrative expense (trustee's fees, legal fees, referee's fees) and in the time lost by executives in liquidation [Kwansa and Cho, 1995]. Offsetting the firm value by integrating bankruptcy cost led to a theory entitled *trade-off theory*.

2.3.2 Trade-off theory

Myers [1984] introduced the *trade-off theory*, in which the tax shield benefit is balanced by the bankruptcy cost. According to this theory, there is an "optimal" debt value (D^*) driving the firm to its maximum value (V_L^*), or equivalently, an "optimal" debt to equity ratio (D^*/E^*) driving the firm to its minimum weighted average cost of capital ($WACC^*$).

This mechanism is illustrated by Figure 2.2. Modigliani-Miller's (M&M) 1^{st} theorem shows that the firm value is independent of its capital structure. The M&M 2^{nd} theorem shows an increasing firm value as the debt amount increases *(TSB effect)*. At the same time, the firm cost of capital ($WACC$) decreases as the debt-equity ratio (D/E) goes up. Finally, the trade-off theory indicates that with both corporate tax and bankruptcy cost, the firm value first goes up *(TSB effect)*, reaches its maximum amount, V_L^*, and then decreases *(EBC effect)*. At the same time, the $WACC$ rate reaches its minimum value, $WACC^*$, and then increases.

To measure the firm value, different approaches and indicators with different visions exist. In section 2.4 we describe the main approaches to identify the most suitable for our needs in this thesis.

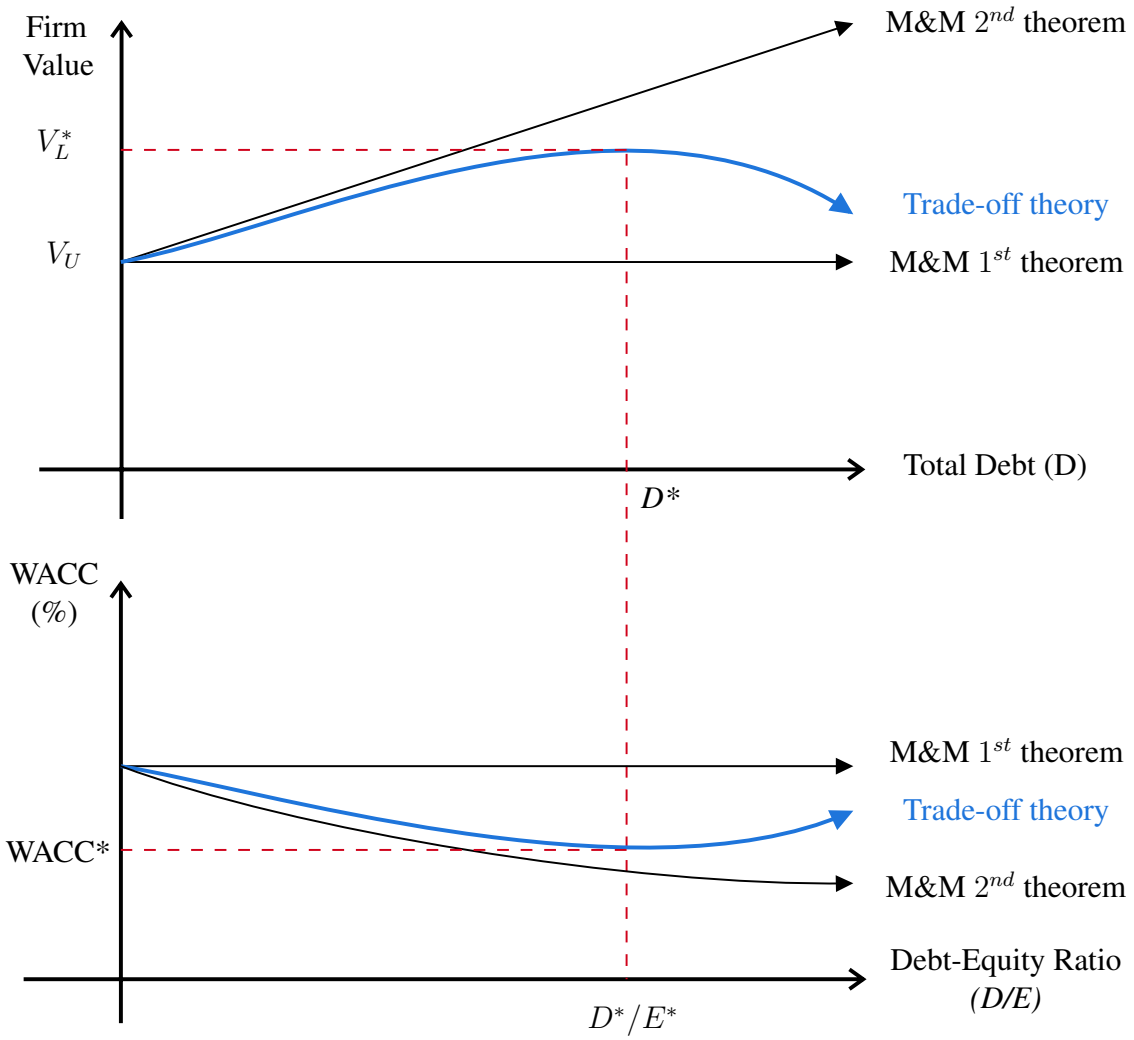

Figure 2.2 – Modigliani-Miller 1^{st} *and* 2^{nd} theorems *vs.* trade-off theory [Altman et al., 2019]

2.4 Approaches to valuation

According to Fernández et al. [2002], there are six approaches to measure the value created for a company where two are among the most commonly used approaches: *value creation* and *discounted cash flows* [Fernández et al., 2002, Eikelmann, 2020]. The former relies on calculating the value created for the company's shareholders. The latter measures the company's value by discounting the future cash flows, illustrating the company's development.

2.4.1 Value creation

A company creates value for its shareholders if its earnings exceed the cost of invested capital [Rappaport, 1999]. Some indicators exist to measure the created value, such as Economic Value Added (EVA) and Market Value Added (MVA).

EVA and MVA are based on the WACC formula:

$$WACC = (1 - \gamma)K_D \frac{D}{D+E} + K_E \frac{E}{D+E},$$

where γ, K_D, K_E, D, and E respectively indicate the firm's tax rate, cost of debt, cost of equity, the value of firm's debt, and value of firm's equity. WACC can be interpreted is a mix of the debt and equity costs, proportional to their contribution to the invested capital.

2.4.1.1 Economic Value Added

Economic value-added (EVA) [Stewart, 1991] is an accounting-based measure of operating performance. It measures the firm's net earnings minus the capital charge for raising its capital. This indicator is an absolute key figure based on earnings which focus on the performance of a single period [Eikelmann, 2020].

The EVA computation requires three basic inputs: earnings or returns on capital, capital invested, and cost of capital. Earnings or returns on capital result from the operating activities; thus, it is measured as the Net Operating Profit After Tax ($NOPAT$). Invested capital, denoted by IC, is generally a mix of debt and equity.

EVA is then calculated according to the following formula:

$$EVA = NOPAT \ - \ WACC \times IC,$$

The impact of financial decisions, i.e., TSB and EBC, should be considered in the WACC formula. The TSB received from debt financing is reflected in a lower cost of debt (and as a result a lower WACC rate), as it is calculated after tax.

Although the TSB effect is simply captured in the WACC formula, considering the EBC is not as simple. According to Koziol [2014], Mari and Marra [2019] incorporating EBC in the WACC formula requires a set of complex corrections. This is a complicated process which is out of the scope of this thesis, hence we do not mention it here.

Although EVA is considered a popular indicator as it simply expresses the performance in value creation, it possesses some disadvantages [Eikelmann, 2020]. We recall some of the main EVA drawbacks. First, EVA is designed to measure a company's performance on a single-period basis. It does not include the forecasted future cash flows and does not measure the present value of the investment. Therefore, it is not suitable to assess long-term projects or startups. Second, it is not a fair indicator to compare different companies. EVA is under the influence of the company's size due to being an absolute key figure. Third, a positive EVA does not essentially mean that the company is performing well. Sometimes a positive EVA is obtained if the invested capital is too small.

2.4.1.2 Application of EVA valuation in SCND models

Regardless of the mentioned drawbacks, EVA is the most commonly used indicator when value-based management is applied to the SCND models.

Note that all the following publications deal with a multi-period planning horizon, while EVA is a single-period performance indicator. Thus the objective *(one of the objectives)* of these publications is to maximize the sum of EVA of each period.

Longinidis and Georgiadis [2011] develop a MILP model to design a supply chain network under demand uncertainty. Their model optimizes the company's net created value, measured by EVA. However, they assume that the WACC rate is a constant parameter. They also evaluate the results of incorporating financial decisions into the SCND process by comparing their proposed model to a non-financial model, which ignores the financial statement analysis. The results of numerical experiments show that the financial model creates more value for the shareholders. However, the Return on Equity (ROE) is higher with the non-financial model.

Longinidis and Georgiadis [2013] study a bi-objective MILP model that captures trade-off values between financial performance, measured with EVA *(unlike their previous work, the WACC is defined as a decision variable)* as the first objective and credit solvency as

the second objective function. Employing the epsilon-constraint method, a set of Pareto optimal solutions are provided. In addition, the optimized solution of EVA maximization is compared with the solution of a cost minimization model. The comparison show that the cost-driven model leads to a very low shareholder value and places into the default area.

Mohammadi et al. [2017] propose a multi-product, multi-period, four-echelon model taking into account both strategic and tactical decision-making levels. The authors address different financial decisions such as cash management, risk management, financial statement control, capital structure, revenue and cost management. These financial dimensions are measured through different objective functions which are firm value, changes in equity, and EVA. Besides, a comprehensive comparison is made between a traditional facility location model (aiming at maximizing profit) and each of the objective functions. This comparison is drawn by defining four different scenarios. Scenario 1 concerns maximizing profit subject to only the operational constraints. Scenarios 2, 3, and 4 regard maximizing firm value, changes in equity, and EVA subject to the whole set of constraints (both operational and financial). Comparing the scenarios shows that scenarios 2, 3, and 4 outperform scenario 1. Although profit is higher in scenario 1, other objectives are more promising with other scenarios.

Badri et al. [2017] address a three-echelon, multi-period, multi-item closed-loop SCND problem. The model, which considers both the tactical and strategic decision levels, aims at maximizing the firm's EVA. The authors define the WACC rate as a constant parameter. They also perform sensitivity analyses for the corporate tax rate and debt interest cost to investigate their impacts on the EVA. These analyses show that EVA decreases when the corporate tax rate is constant while the debt interest rate increases. Increasing the corporate tax rate while fixing the debt interest rate leads to similar behavior of EVA.

Yousefi and Pishvaee [2018] propose a fuzzy MILP model to design a global supply chain network maximizing EVA. Different variables such as assets, capital structure, and equity are compared with and without EVA. They show that maximizing EVA leads to higher value for those variables.

The MINLP model developed by Polo et al. [2019] studies the consequences of economic uncertainty on the financial health of supply chains. The model provides a robust design of a multi-period closed-loop supply chain to maximize EVA under demand uncertainty. Following Laínez et al. [2010], the WACC rate is assumed as a fixed parameter. In addition to EVA, the authors also consider other financial indicators such as NPV and WACC to

be evaluated.

EVA is also used as the objective function in the multi-period model proposed by Borges et al. [2019], which extends the model of Longinidis and Georgiadis [2011] considering debt repayments and new capital entries as decision variables. Still, the WACC is assumed to be a fixed parameter. Their model leads to higher EVA in comparison to the model of Longinidis and Georgiadis [2011].

2.4.1.3 Market Value Added

Market Value Added (MVA) is a tool to transform EVA to a multi-period basis. MVA equals the company's value less the value of invested capital. Mathematically speaking it measures the present value of future EVA [Eikelmann, 2020].

$$MVA = \sum_{t} \frac{EVA}{(1 + WACC)^t}.$$

Discounting the projected EVAs of the firm using WACC implicitly assumes a fixed leverage ratio ($\frac{D}{D+E}$) during the forecasted time. Expressing debt proportional to the firm value ($=D+E$) means that the debt level evolves according to firm value over time. While firm valuation using the WACC approach is valid as long as the leverage ratio is stable.

2.4.1.4 Application of MVA valuation in SCND models

Sabogal-De La Pava et al. [2021] address a multi-period, multi-product sustainable SCND problem, developed as a mixed-integer nonlinear mathematical model. The objective is to maximize the MVA of the firm. Nevertheless, the WACC rate is considered as a fixed (exogenous) parameter. The authors also do a set of sensitivity analyses, including the WACC rate. Regarding and disregarding the sustainability aspects, they show how MVA behaves when the WACC rate is altered. For every 1% increase in the WACC, the sustainable MVA is reduced by 4.44% while the non-sustainable MVA is reduced by 1.28%.

2.4.2 Discounted cash flows

This valuation approach seeks to determine the company's value by forecasting its future cash flows and then discounting them at a discount rate that matches the flow's risk.

Incorporating TSB and EBC in the process of company valuation leads to three main discounted cash flow-based valuation methods [Altman et al., 2019]: (i) Free Cash Flows

(FCF), (ii) Capital Cash Flows (CCF), and (iii) Adjusted Present Value (APV).

The valuation process of the first two methods relies on the WACC calculation, while APV entails adjusting the firm's present value. Figure 2.3 illustrates this classification.

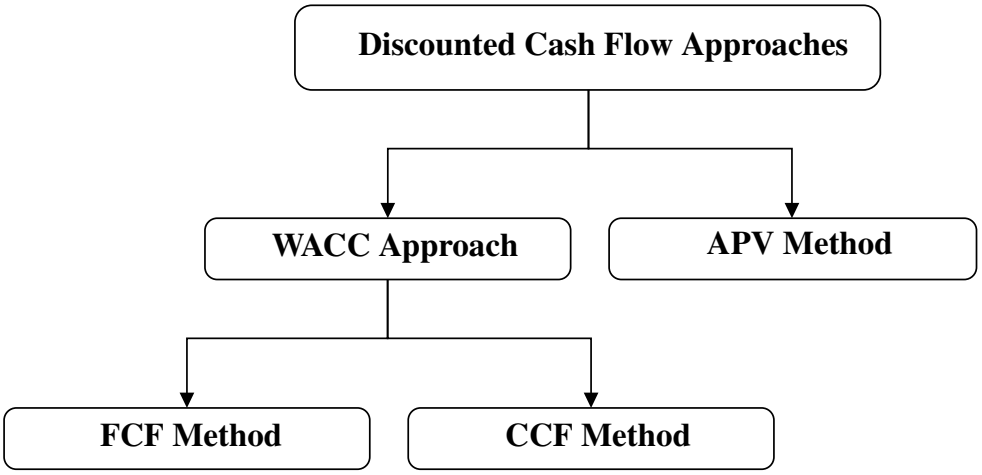

Figure 2.3 – Discounted Cash Flow Approaches (adapted from Eikelmann [2020])

2.4.2.1 Free Cash Flows

According to this method, the firm's FCFs are discounted to their present value at the cost of capital rate. FCFs are defined as the sum of the cash flows generated by the firm, which are available to all capital providers. Therefore, $WACC$, which is a mix of debt and equity cost, is the appropriate discount rate.

Note that, the FCFs are calculated before financing. In other words, they are operating cash flows (i.e. the cash flows generated by the operations). Thus, the financial effects, i.e., TSB and EBC should be reflected in the WACC rate (see section 2.4.1.1).

Finally, the firm value, denoted by V, is determined by discounting the FCFs of the firm at the WACC rate.

$$V = \sum_t \frac{FCF_t}{(1 + WACC)^t}.$$

Calculating the firm value by discounting the projected FCFs at the WACC rate has the same difficulty as the MVA calculation (see section 2.4.1.3). Therefore, this method is suitable for the cases with a constant leverage ratio ($\frac{D}{D+E}$) during their forecasted time.

Application of FCF valuation in SCND models: In the field of SCND, Laínez et al. [2007] propose an integrated strategic-tactical model in which the company's value, called Corporate Value (CV) in that paper, is adopted as the objective function. To cope with the difficulty of a variable WACC rate, they consider it as a fixed parameter over the planning horizon, which is a strong assumption. The authors compare their approach with the "traditional" one that computes the maximum-profit and NPV design without financial considerations. This comparison is made applying the ϵ-constraint approach. Accordingly, a constraint is added to the model to seek the solutions with higher profit/NPV. Their results show that the solutions optimizing CV are much better than those that maximize profit/NPV in terms of corporate value. This means that higher profit/NPV compromises the corporate value.

2.4.2.2 Capital Cash Flow

CCF is a valuation method which considers the sum of cash flows that are distributed to both equity holders and debt holders. Unlike the previous method which excludes TSB from the cash flows (considers FCFs to the firm), CCF takes the overall after-tax cash flows into account.

$$CCF = FCF + TSB.$$

According to this method, the debt ratio is assumed to be constant, so that interest and tax shields have the same risk as the firm. Thus, the firm's value V is calculated by discounting both the FCFs and TSB using a single discount rate:

$$V = \sum_t \frac{CCF_t}{(1 + WACC)^t}.$$

Note that, as TSB is included in CCF, the appropriate discount rate is the before-tax WACC:

$$WACC = K_D \frac{D}{D+E} + K_E \frac{E}{D+E}.$$

Similar to the FCF valuation, EBC can be incorporated into the CCF method by adjusting its discount rate.

Application of CCF valuation in the SCND models: To the best of our knowledge, there is no publication applying the CCF valuation method in the context of SCND problem.

2.4.2.3 Adjusted Present Value

APV follows directly from the work of Modigliani and Miller [Altman et al., 2019]. The main principle of the APV is to adjust the unlevered value of the firm by considering the debt effect. APV does not attempt to capture the financial effects (TSB and EBC) by adjusting the discount rate. As illustrated by Figure 2.4, it begins the firm valuation process assuming that the firm is all equity-financed (called firm's unlevered value), then it adds the effect of debt financing to the unlevered value.

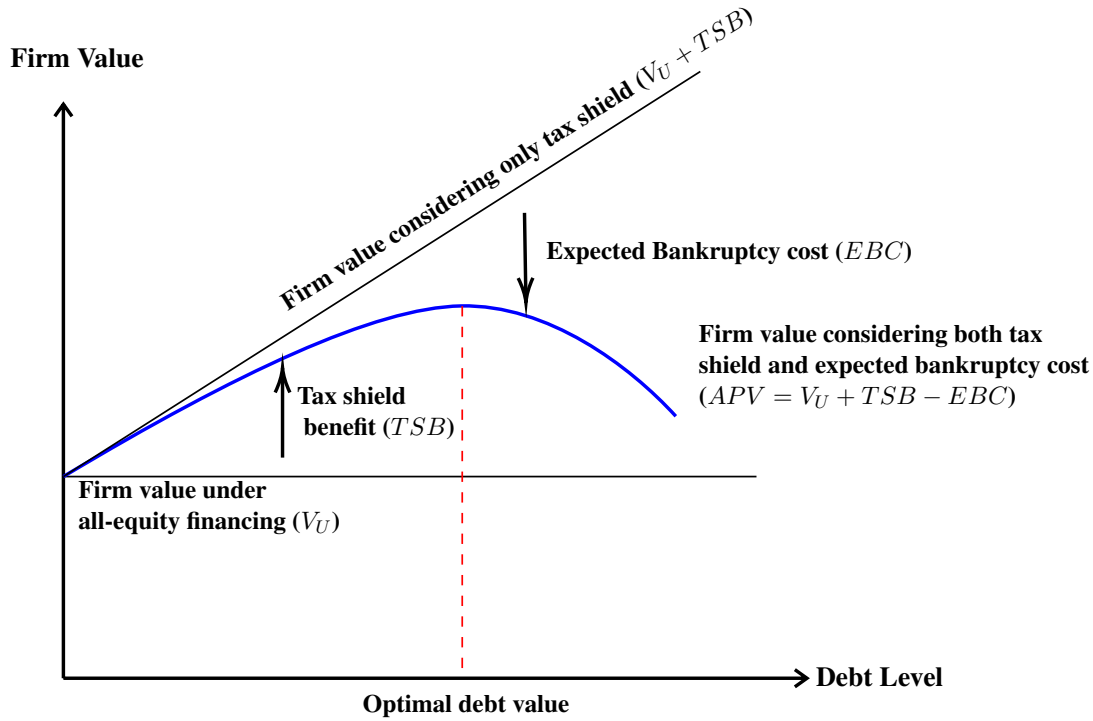

Figure 2.4 – Adjusted Present Value (APV) method

Thus, the total firm value V equals the sum of the FCFs discounted at cost of equity rate plus the value of debt tax shields discounted at cost of debt minus the expected bankruptcy cost.

$$APV \equiv V = \sum_t \frac{FCF_t}{(1+K_E)^t} + \frac{TSB}{(1+K_D)^t} - EBC,$$

Due to splitting the firm value into three parts and separating the unlevered firm value from the value contributed by financial decisions, APV works under both constant and variable debt ratios. In addition to that, APV possesses two main virtues [Baldi, 2005]: (i) it provides disaggregated information about the factors contributing to the firm value; (ii) it permits a detailed analysis of the value deriving from the choice of a particular financial structure by isolating the contribution of fiscal benefits to the corporate value creation. Moreover and according to Altman et al. [2019], the APV approach is often implemented more easily and accurately rather than FCF and CCF methods particularly when the firm capital structure is not stable and changes significantly during the forecasted time. In addition, when the financial impact is major (e.g., often for the case of large global investments), the APV approach suits more to value a firm [Brealey et al., 2016]. Relating to the assessment of financial distress, APV is more flexible, enabling to consider the indirect cost of bankruptcy [Damodaran, 2012].

Application of APV valuation in the SCND models: Like the CCF valuation method, the APV method has not been the subject of any SCND model.

2.5 Conclusion and discussion

In this chapter, we reviewed the main firm valuation approaches and financial indicators related to value-based management. This review shed light on the lack of publications incorporating value-based management in the SCND problems. Table 2.1 summarizes the reviewed financial indicators alongside the related publications.

Financial Indicator	*Articles in the SNCD literature*
EVA	Longinidis and Georgiadis [2011, 2013] Mohammadi et al. [2017], Badri et al. [2017] Yousefi and Pishvaee [2018], Polo et al. [2019] Borges et al. [2019]
MVA	Sabogal-De La Pava et al. [2021]
FCF	Laínez et al. [2007], Mohammadi et al. [2017]
CCF	—
APV	—

Table 2.1 – Summary of the financial indicators used in SCND models

Three indicators, EVA, MVA, and firm value using the FCF method, have been used

in the SCND models. CCF and APV have not been investigated yet.

All indicators excepted APV are based on the WACC calculation. EVA differs from other indicators, as it is defined on a single-period basis. This feature of EVA suggests that it is not the most suitable for a long-term investment evaluation.

The other WACC-based indicators are defined on a multi-period basis, and all are discounted at the WACC rate. The WACC discounting implicitly assumes a certain condition, i.e., a constant debt ratio. Setting up a constant debt ratio over the planning horizon is typical for mature companies and well-established businesses. In contrast, this is not the case for young companies and emerging businesses.

Despite that, all the reviewed articles used a WACC-based indicator. However, the WACC rate is often assumed as a constant parameter in these references. This strong assumption leads the companies to always employ debt as the same proportion to the firm's total assets. Consequently, there is no capital structure optimization regarding the advantages and disadvantages of debt and equity financing.

The other limitation with the WACC-based indicators is related to bankruptcy assessment. Bankruptcy cost contains both direct and indirect costs. Although WACC can be adjusted (through a complex process) to incorporate the direct bankruptcy cost, it cannot capture the effect of indirect bankruptcy cost.

APV does not suffer from the issues mentioned above. Unlike the WACC-based indicators, APV does not incorporate the TSB and EBC effects in the discount rate. Instead, it only adjusts the unlevered firm value. It measures the firm value by adding TSB and subtracting the EBC from the unlevered value. This enables APV to suit both stable and non-stable debt ratios. Concerning the bankruptcy effect, APV is more appropriate for assessing the bankruptcy by incorporating its direct and indirect costs.

All in all, among all mentioned approaches and indicators, APV fits more to the goal of this thesis as it suits the stable and non-stable debt ratios and is more appropriate to assess the financial distress. APV measures the firm's value as a function of its profitability, tax shield benefits, and bankruptcy. It enriches the decision-makers with disaggregated information plus the firm's optimal value, which is directly calculated as a function of the three elements mentioned above.

In the following chapter, we seek to use APV as the objective function of a dynamic SCND model that maximizes the firm value over a strategic horizon.

Chapter 3

An APV-based supply chain network design model

3.1 Introduction

In this chapter, we introduce a SCND mathematical model integrating financial decisions through APV maximization. The main expected contribution of this model is to extend traditional facility location models by considering the financial impact of facility location decisions on the whole firm's value. More precisely, we propose a new SCND model aiming at determining how to finance facility location decisions while maximizing APV.

The general formula for the APV is graphically represented by Figure 3.1. The unlevered firm value, also known as base-case Net Present Value (NPV) [Brealey et al., 2016], is the value generated by the operational decisions only. Hereafter, it is thus called *Operationally Generated Value* (OGV). In order to compute it, the operational future cash flows are discounted at the unlevered equity cost (or debt free cost of capital). The *Financially Generated Value* (FGV) is composed of the two last terms (present value of debt advantages and disadvantages).

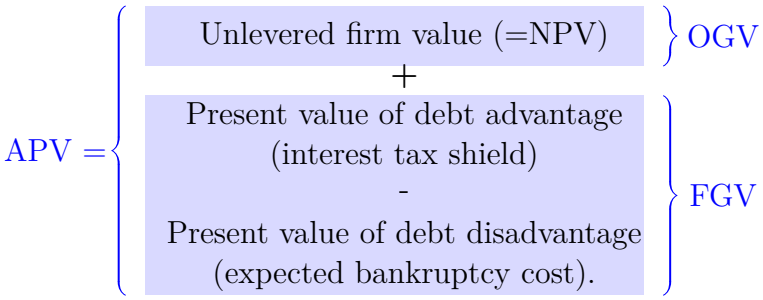

Figure 3.1 – Calculation of the APV

As illustrated by Figure 3.1, the APV is determined by two types of decisions in an SCND model. First, logistic decisions consist of selecting facilities from a set of candidate

locations to deliver goods to a set of customers. This impacts only the OGV. Second, financial decisions determine the level of debt in order to finance the logistic investments staggered over time. This impacts only the FGV. This motivated us to design two solution approaches, consisting in solving the MILP model in a sequential way (OGV then FGV), called the sequential approach, or at once, called the integrated approach.

The outline of the chapter is as follows. Section 3.2 first describes the general problem settings, then presents the mathematical model explaining the constrains related to the OGV and the FGV, respectively. Section 3.3 details the main linearization procedures employed to linearize the model. Section 3.4 illustrates the interactions between logistic and financial decisions, through a small example. Finally, section 3.5 concludes the chapter.

3.2 Problem definition and mathematical formulation

In this section, we detail the mathematical model maximizing APV subject to logistic and financial constraints. Section 3.2.1 introduces problem settings, and the time horizon considered by the model. Sections 3.2.2 and 3.2.3 enumerate the model constraints related to the Operationally Generated Value (OGV) and the Financially Generated Value (FGV), respectively.

3.2.1 Problem features

3.2.1.1 General Settings

In the sequel, the model is based on a strategic time horizon (time periods are typically years), divided in two complementary sets: $\mathcal{T}$ for logistic and financial decisions and $\mathcal{T}'$ for all financial impacts of strategic decisions in $\mathcal{T}$. We consider a supply chain with two echelons, including a set $\mathcal{J}$ of candidate production facilities and set $\mathcal{I}$ of customers.

We assume that reliable forecasts of customers' demand are available for the whole time horizon $\mathcal{T}$. The demand of customer $i \in \mathcal{I}$ at period $t \in \mathcal{T}$ is denoted D_{it}, assumed deterministic. Each candidate production facility has a known capacity $Capa_j$ for all $j \in \mathcal{J}$. Our multi-period model particularly addresses a supply chain whose markets, customers' demands and facilities are subject to large variations along time. Thus, we do not force the company to serve all customers at every period. Unsatisfied customers'

demands are simply lost and back orders are forbidden. However, at each period, a customer's demand is either entirely fulfilled or not at all (all-or-nothing principle). Besides, we apply the idea of incremental service introduced by Albareda-Sambola et al. [2009]: the allocation of any customer to the facilities $j \in \mathcal{J}$ might change in different periods. Nevertheless, customers that are being served in a period must be served at any subsequent period. We don't consider single-sourcing constraints: customers can be served by several facilities.

The number of opened facilities is bounded by the value J_{max}. When a facility is open, it is not possible to close it during the time horizon.

Under this framework, the goal of the SCND model is to determine which candidate facilities will be opened, when they will be opened and how these logistic decisions will be financed. The company seeks to maximize its APV. All additional notations (parameters, variables) are introduced on the fly and summarized in Tables 3.1–3.7.

3.2.1.2 Time horizon

Maximizing APV requires computing the present value of the future operational and financial cash flows over multiple periods. The time horizon $\mathcal{T} = \{1, \ldots, T\}$ represents the set of periods in which SCND decisions are applicable, i.e., the company can borrow and invest money at any period $t \in \mathcal{T}$.

Even so, the logistic and financial decisions taken in this time horizon will have a much longer impact on the cash flows of the company. Assume that the company opens a new facility at a period $t \in \mathcal{T}$ and borrows some money to finance this decision. Given a reimbursement duration of N time periods and the lifetime L_j of facility $j \in J$, the impact of this decision on the company's debt will be observed until period $t + N$ while the associated cash flow will be observed until period $t + L_j$. This is the time horizon $\mathcal{T}$ needs to be extended, as represented in Figure 3.2. We introduce the time horizon extension $\mathcal{T}' = \{T+1, \ldots, T+N\}$ corresponding to the set of time periods during which the financial impact of logistics decisions can be observed after the time horizon $\mathcal{T}$. Neither facility opening nor borrowing occurs during $\mathcal{T}'$.

Note that period 0 represents the initial state of the supply chain which results from past decisions. Without loss of generality, we assume an initial situation with no selected facility at period 0 and no customer served. All financial variables (cash, loan, repayment of loan, etc.) are set to value 0.

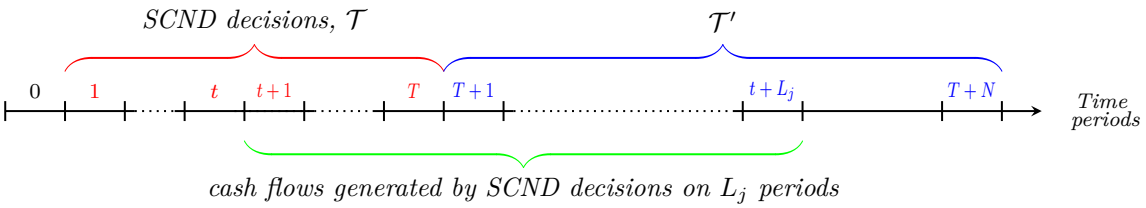

Figure 3.2 – Time scale of supply chain decisions and their financial impact

$\mathcal{I}$	Set of customers
$\mathcal{J}$	Set of candidate facilities
$\mathcal{T}$	Set of time periods (supply chain horizon)
$\mathcal{T}'$	Extended set of time periods (financial horizon)

Table 3.1 – Data sets

3.2.2 OGV: Operationally Generated Value

In this section, we detail how the future cash flows generated by the operational decisions are obtained. We first explicit the constraints related to the selection of candidate facilities and the allocation of customers to selected facilities. Then, we calculate the revenues and expenses associated with the selected facilities, which leads to the calculation of the OGV.

3.2.2.1 Selection of candidate facilities

The quantity that the company can sell depends on the number and on the capacity of facilities opened at each period. We define the binary variables y_{jt}, which take value 1 if the facility $j \in \mathcal{J}$ is operating at period $t \in \mathcal{T}$, and 0 otherwise. Initially, $y_{j0} = 0$ for all $j \in \mathcal{J}$. Therefore, a facility is opened at time $t \in \mathcal{T}$ if $y_{j,t} - y_{j,t-1} = 1$. We assume a lifetime $L_j > T$ for each candidate facility. The main consequence is that selected facilities cannot be closed during the time horizon $\mathcal{T}$. Besides, the number of facilities selected is bounded above by a number J_{max}. These assumptions are modeled by constraints (3.1) and (3.2).

$$y_{j,t-1} \leq y_{jt} \qquad \forall j \in \mathcal{J}, t \in \mathcal{T} \tag{3.1}$$

$$\sum_{j \in \mathcal{J}} y_{j,T} \leq J_{max}. \tag{3.2}$$

3.2.2.2 Allocation of customers

The binary variable x_{it} takes value 1 if customer $i \in \mathcal{I}$ is served at period $t \in \mathcal{T}$, and 0 otherwise. According to constraints (3.3) the customers served at some time period will still be served at all subsequent time periods. Due to trade rules between geographical areas as well as various logistic constraints, some customers might not be delivered by some facilities. Thus, we introduce an accessibility binary parameter V_{ij} which takes value 1 if the customer $i \in \mathcal{I}$ is accessible from facility $j \in \mathcal{J}$. Customers can be delivered from several different facilities at distinct periods. Let q_{ijt} denote the quantity delivered by facility $j \in \mathcal{J}$ to customer $i \in \mathcal{I}$ at period $t \in \mathcal{T}$. This quantity is strictly positive only if facility j is opened (when $y_{jt} = 1$) and if $V_{ij} = 1$. The quantity delivered from $j \in \mathcal{J}$ to $i \in \mathcal{I}$ at period $t \in \mathcal{T}$ cannot exceed the demand D_{it} (Constraints (3.4)). According to the all-or-nothing principle, no partial satisfaction of a particular customer's demand is authorized. Constraints (3.5) calculate the total quantity delivered to each customer, which is either 0 (when $x_{it} = 0$) or the total demand D_{it} (when $x_{it} = 1$). The capacity constraints (3.6) enforce the total quantity shipped by a selected facility $j \in \mathcal{J}$ to be at most equal to its capacity $Capa_j$. Note that it is possible to model several possible capacities for each facility, by setting several candidate facilities, with distinct capacities, at the same location.

$$x_{i,t-1} \leq x_{it} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.3}$$

$$q_{ijt} \leq V_{ij}\ D_{it}\ y_{jt} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J}, t \in \mathcal{T} \tag{3.4}$$

$$\sum_{j \in \mathcal{J}} q_{ijt} = D_{it}\ x_{it} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.5}$$

$$\sum_{i \in \mathcal{I}} q_{ijt} \leq Capa_j\ y_{jt} \qquad \forall j \in \mathcal{J}, t \in \mathcal{T}. \tag{3.6}$$

3.2.2.3 Logistic costs and revenues

For each candidate facility $j \in \mathcal{J}$, we consider a fixed opening cost O_j which is paid once if the facility is selected, and yearly fixed costs F_j paid at every period when the facility is operating. In addition, each operating facility has a processing cost μ_j for each unit of product processed by this facility. The distance between two locations $i \in \mathcal{I}$ and $j \in \mathcal{J}$ is denoted as $Dist_{ij}$. We assume that the transportation cost between two locations is proportional to the distance traveled and the load carried, with a unit transportation cost

ω over the whole network.

Constraints (3.7) calculate the total amount of logistic expenses e_{jt} of facility $j \in \mathcal{J}$ at period $t \in T$. This amount is the sum of the yearly fixed cost, the processing cost and the transportation cost.

$$e_{jt} = F_j \; y_{jt} + \mu_j \; \sum_{i \in \mathcal{I}} q_{ijt} + \omega \; \sum_{i \in \mathcal{I}} (Dist_{ij} \; q_{ijt}) \qquad \forall j \in \mathcal{J}, t \in \mathcal{T}. \tag{3.7}$$

Considering a selling price P_i to customer $i \in \mathcal{I}$, the total revenue r_{jt} generated by facility $j \in \mathcal{J}$ at period $t \in \mathcal{T}$ is calculated with constraints (3.8).

$$r_{jt} = \sum_{i \in \mathcal{I}} (P_i \; q_{ijt}) \qquad \forall j \in \mathcal{J}, t \in \mathcal{T}. \tag{3.8}$$

Binary variables		
y_{jt}	$= 1$ if facility $j \in \mathcal{J}$ is operating at period $t \in \mathcal{T} \cup \mathcal{T}'$, 0 otherwise	
x_{it}	$= 1$ if customer $i \in \mathcal{I}$ is served at period $t \in \mathcal{T}$, 0 otherwise	
Continuous variables		
e_{jt}	Expenses occurred at period $t \in T$ for facility $j \in \mathcal{J}$	$[0, \infty[$
q_{ijt}	Quantity shipped from facility $j \in \mathcal{J}$ to customer $i \in \mathcal{I}$ at period $t \in T$	$[0, \infty[$
r_{jt}	Revenues obtained at period $t \in T$ related to facility $j \in \mathcal{J}$	$[0, \infty[$

Table 3.2 – Variables related to logistic decisions

3.2.2.4 Calculation of the OGV

In an accounting approach, depreciation represents a yearly decrease of tangible assets' value over time. Among different methods to depreciate the firm's assets, the constraints (3.9) model the straight-line approach (see, e.g., Laínez et al. [2007]) to calculate the depreciation of each facility $j \in \mathcal{J}$ as a linear function of its initial value O_j, salvage value SV_j, and lifetime L_j.

$$Dep_j = \frac{O_j - SV_j}{L_j} \qquad \forall j \in \mathcal{J}. \tag{3.9}$$

In constraints (3.10), the Earning Before Interest and Taxes (EBIT) associated with facility $j \in \mathcal{J}$ at period $t \in \mathcal{T}$, denoted $EBIT_{jt}$, is the difference between the revenues

$Capa_j$	Yearly production capacity of facility $j \in \mathcal{J}$
D_{it}	Demand of customer $i \in \mathcal{I}$ at period $t \in \mathcal{T}$
Dep_j	Annual depreciation of facility $j \in \mathcal{J}$
F_j	Fixed yearly running cost of facility $j \in \mathcal{J}$
J_{max}	Max number of facilities to be located
L_j	Lifetime of each facility $j \in \mathcal{J}$
O_j	Opening cost of facility $j \in \mathcal{J}$
P_i	Product selling price for customer $i \in \mathcal{I}$
SV_j	Salvage Value of each facility $j \in \mathcal{J}$
V_{ij}	Equals 1 if facility j can serve customer $i \in \mathcal{I}$, 0 otherwise
μ_j	Processing cost of facility $j \in \mathcal{J}$
ω	Unit transportation cost

Table 3.3 – Parameters related to logistics

and expenses of facility $j \in \mathcal{J}$ (before interest and tax) at period t and the depreciation factor Dep_j (which occurs if the facility j is opened at period $t-1$).

$$EBIT_{jt} = r_{jt} - e_{jt} - Dep_j \; y_{j,t-1} \quad \forall j \in \mathcal{J}, t \in \mathcal{T}. \tag{3.10}$$

From this accounting result, the operating cash flow is expressed by constraints (3.11).

$$CF_{jt} = (1-\eta)EBIT_{jt} + Dep_j \; y_{j,t-1} \quad \forall j \in \mathcal{J}, t \in \mathcal{T}. \tag{3.11}$$

The first term is the accounting result after tax (with a tax rate η). The second term reintroduces the depreciation because it is not a cash outflow. The free cash flows FCF_{jt} is obtained by subtracting capital expenses from the operating cash flow.

$$FCF_{jt} = (1-\eta)EBIT_{jt} - (O_j(y_{jt} - y_{j,t-1}) - Dep_j \; y_{j,t-1}) \quad \forall j \in \mathcal{J}, t \in \mathcal{T}, \tag{3.12}$$

The free cash flow measures the firm's ability to generate cash. FCF_{jt} is defined as the difference between both operating and non-operating cash inflows and outflows associated with each facility.

A facility $j \in \mathcal{J}$ opened at period $\tau \in \mathcal{T}$ has a lifetime $L_j > T$. As illustrated by Figure 3.2, it generates potential cash flows during $[\tau; T]$ and a constant cash flow CF_{jT} after period T, as long as is it active.

The calculation of OGV requires determining which facilities are operating during

each period $t \in \mathcal{T} \cup \mathcal{T}'$. Therefore, we extend the definition of binary variables y_{jt} to $\mathcal{T}'$ as follows: for any $j \in \mathcal{J}, t \in \mathcal{T}'$, y_{jt} is equal to 1 if facility j is operating at period t, and 0 otherwise. If $y_{jT} = 1$ and the facility was opened at period $\tau \in \mathcal{T}$, then $y_{jt} = 1$ for all $T + 1 \leq t \leq \tau + L_j - 1$, and 0 otherwise. Then, for all $t \geq \tau + L_j$, $y_{tj} = 0$. If $y_{jT} = 0$, all variables y_{jt} are equal to 0. Constraints (3.13) and (3.14) model these rules:

$$y_{j,t-1} \geq y_{jt} \qquad \forall t \in \mathcal{T}' \backslash \{T+1\} \tag{3.13}$$

$$\sum_{t \in \mathcal{T}} y_{jt} + \sum_{t \in \mathcal{T}'} y_{jt} = L_j \; y_{jT} \qquad \forall j \in \mathcal{J}. \tag{3.14}$$

Let K_E denote the equity cost of capital of the unlevered company. The Operationally Generated Value (OGV) is defined by:

$$OGV = \sum_{j \in \mathcal{J}} \left(\sum_{t \in \mathcal{T}} \frac{FCF_{jt}}{(1+K_E)^t} + \sum_{t \in \mathcal{T}'} \frac{CF_{jT} \; y_{jt}}{(1+K_E)^t} \right). \tag{3.15}$$

CF_{jt}	Cash flow generated by facility $j \in J$ at period $t \in T$	$]-\infty, \infty[$
$EBIT_{jt}$	Earnings before interest and tax by facility $j \in \mathcal{J}$ at period $t \in \mathcal{T}$	$]-\infty, \infty[$
FCF_{jt}	Free cash flow associated with facility $j \in \mathcal{J}$ at period $t \in \mathcal{T}$	$]-\infty, \infty[$
OGV	Operationally generated value of the firm	$]-\infty, \infty[$

Table 3.4 – Variables used in the OGV calculation

3.2.3 FGV: Financially Generated Value

If a facility $j \in \mathcal{J}$ is opened at period $t \in \mathcal{T}$, the firm has to decide how to finance its opening cost O_j. Following the trade-off theory of capital structure, the company can choose between two classical modes of supply chain financing. *Debt financing*, detailed in section 3.2.3.1, amounts to borrow money to a bank. For this purpose, we define the variables $borrow_t$, which represent the amount of money borrowed at period $t \in \mathcal{T}$. In *Equity financing*, detailed in Section 3.2.3.2, money is supported by shareholders, in the form of internal financing (company's cash holdings) represented by the variables IE_t, and/or external equity represented by the variables EE_t.

Equation (3.16) states that facility sunk costs are funded by the debt, internal funding or by external equity.

$$\sum_{j \in \mathcal{J}} O_j(y_{jt} - y_{j,t-1}) = borrow_t + IE_t + EE_t \qquad \forall t \in \mathcal{T}. \tag{3.16}$$

Section 3.2.3.3 will explain how the split between debt and equity financing will affect the amount of interest and thus tax savings on the one hand and the Expected Bankruptcy Cost (EBC) value on the other hand. Incorporating financial decisions into a SCND problem amounts to select a mix of debt and equity that optimizes the FGV.

3.2.3.1 Debt financing

We recall that the annuity amount A associated with a loan amount B, an interest rate α and a number N of equally sized payments is given by:

$$A = B \, \frac{\alpha(1+\alpha)^N}{(1+\alpha)^N - 1}.$$

Assuming that the company will only use loans with the same maturity N, $N \geq T$, interest rate α and constant annuity repayment method, the amount borrowed at period $t \in \mathcal{T}$ will be repaid from $t+1$ to $t+N$. The company may borrow several times within the horizon $\mathcal{T}$, then, the total annuity paid at each period is the sum of individual annuities linked to several loans contracted at different periods. The total annuity repaid at time t, represented by the variables $repay_t$, follows three different schemes depending on the period. Until T, the repayment function is non-decreasing because the company can decide to borrow at each period. It reaches its maximum at time T and remains constant until period $N+1$. After this date, it decreases when a debt is totally repaid. Repayment formula is given by constraints (3.17). It is initialized with $repay_0 = 0$.

$$repay_t = \begin{cases} repay_{t-1} + borrow_{t-1} \, \frac{\alpha(1+\alpha)^N}{(1+\alpha)^N - 1} & t = 1, ..., T \\ repay_T + borrow_T \, \frac{\alpha(1+\alpha)^N}{(1+\alpha)^N - 1} & t = T+1, ..., N+1 \\ repay_{N+1} - repay_{t-N} & t = N+2, ..., T+N. \end{cases} \tag{3.17}$$

Figure 3.3 illustrates the repayment of two loans, with $T = 5$ and $N = 7$. The first repayment (represented in blue) starts at period 1 with an annuity of 10. The second repayment (represented in orange) starts at period 3 with an annuity of 8. Therefore, the

value of variables $repay_t$ is 10 for any $t \in \{1, 2\}$, 18 for any $t \in \{3, 7\}$, 8 for any $t \in \{8, 9\}$, and 0 later.

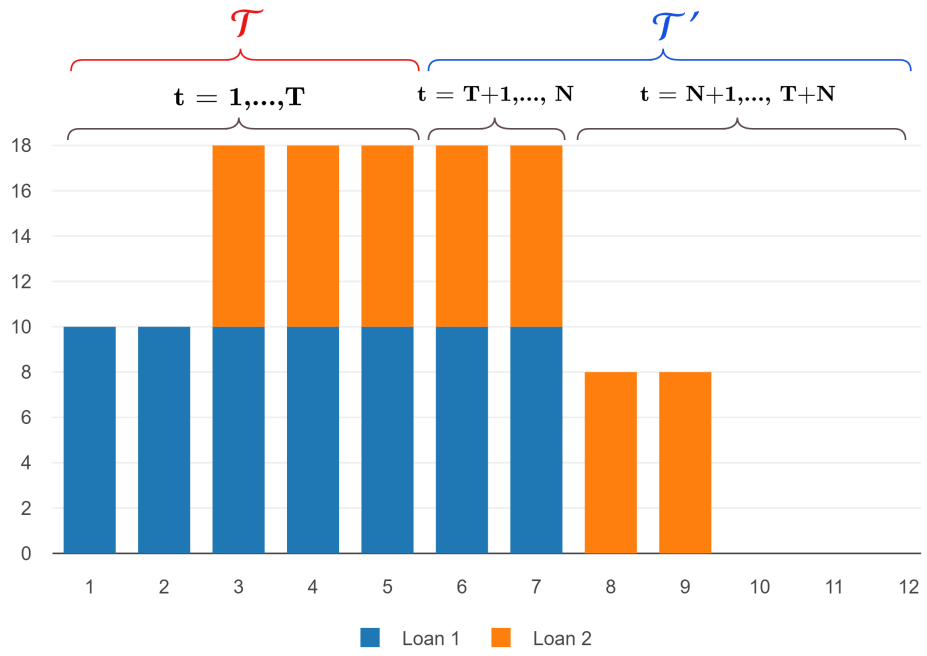

Figure 3.3 – Repayment mechanism

We define $loanBalance_t$ and $interest_t$ respectively as the total debt still alive and the value of the interest at period $t \in \mathcal{T} \cup \mathcal{T}'$. Given the interest rate α is the same for every loan, the constraints (3.18) calculate $interest_t$. The constraints (3.19) calculate the value of the loan balance at period t as the value at the preceding period $loanBalance_{t-1}$, augmented by the new loan $borrow_t$ at period t, and decreased by the debt amortization during the period, which is equal to $repay_t$ - $interest_t$.

$$interest_t = \alpha \; loanBalance_{t-1} \qquad \forall t \in \mathcal{T} \cup \mathcal{T}' \quad (3.18)$$

$$loanBalance_t = loanBalance_{t-1} + borrow_t - (repay_t - interest_t) \quad \forall t \in \mathcal{T} \cup \mathcal{T}'. \quad (3.19)$$

Note that constraints (3.19) require variables $borrow_t$ to be defined for the whole set of periods $\mathcal{T} \cup \mathcal{T}'$. Thus, it is artificially extended to $\mathcal{T}'$, with value $borrow_t = 0, \forall t \in \mathcal{T}'$.

3.2.3.2 Equity financing

As presented in equation (3.16), equity financing is divided in two parts: internal equity financing that is defined as the amount of cash that is retained inside the company instead of being paid to shareholders and external equity financing, EE_t, that is equal to the amount of cash contributed by shareholders at period $t \in T$. In order to compute internal equity financing, we first compute the cash flows generated by the company owned by shareholders, then the fraction of those cash flows that are retained inside the company and finally how retained cash flows are accumulated in the form of cash holdings.

Cash flows generated by the company owned by shareholders are equal to the remaining cash flows (residual cash flows) once all stakeholders, including lenders and State, have been remunerated. By definition, the residual cash flow, denoted $NOPAT_t$, Net Operating Profit After Taxes of period $t \in \mathcal{T}$, is obtained by removing the interest expenses from the EBIT at period $t \in \mathcal{T}$, and then multiplying the result by the term $(1 - \eta)$, where η is the firm tax rate:

$$NOPAT_t = (1 - \eta)(\sum_{j \in \mathcal{J}} EBIT_{jt} - interest_t) \quad \forall t \in \mathcal{T}. \tag{3.20}$$

Let δ denote the payout ratio, i.e., the fraction of earnings paid as dividends. In constraints (3.21), the level of cash at period $t \in \mathcal{T}$ results from the available cash $cash_{t-1}$ at the end of the preceding period, plus the retained earnings $(1 - \delta)NOPAT_t$, plus the external equity EE_t supported by shareholders, plus the net changes in long-term liabilities, $borrow_t - (repay_t - interest_t)$, minus the sum of net assets values associated with all facilities.

$$\begin{aligned} cash_t = cash_{t-1} + (1 - \delta)NOPAT_t + EE_t + borrow_t - (repay_t - interest_t) \\ - \sum_{j \in \mathcal{J}} (O_j(y_{jt} - y_{j,t-1}) - Dep_j\ y_{j,t-1}) \quad \forall t \in \mathcal{T}. \end{aligned} \tag{3.21}$$

In constraints (3.16), IE_t was defined as the amount of money invested from the internal source of the company at period $t \in \mathcal{T}$, in order to fund the firm's strategic decisions. Therefore, IE_t cannot exceed the cash available at the end of the preceding period, $cash_{t-1}$, as stated by constraints (3.22).

$$IE_t \leq Max(0, cash_{t-1}) \quad \forall t \in \mathcal{T}. \tag{3.22}$$

3.2.3.3 Calculation of FGV and APV

As explained and illustrated in Section 3.1, the FGV is the sum of the interest tax shield and the Expected Bankruptcy Costs (EBC). EBC is the present value of direct (legal and accounting costs) and indirect bankruptcy costs, a continuum of costs that increase at an accelerating rate as exposure to bankruptcy increases, e.g., increased interest expenses, lost credit, lost sales, inefficient operations. Direct costs take the form of administrative expenses (trustee's fees, legal fees, referee's fees), and in the time lost by executives in liquidation [Kwansa and Cho, 1995].

Damodaran [2012] calculates EBC as the product of the probability of bankruptcy, denoted p, by the bankruptcy costs $\gamma \times OGV$, where $0 < \gamma < 1$ is a known fixed parameter.

We chose to express bankruptcy costs as a fraction of the firm value before bankruptcy as it is usually done both in theoretical [Leland, 1994] and empirical studies [Altman, 1984, Weiss, 1990]. The various approaches only differ on the measures of the firm value (book versus market value, total versus equity value), in the model, we choose the market operational value of the company.

The second part of EBC concerns the probability of bankruptcy. There exist several bankruptcy prediction methods in the financial literature, e.g. Altman [1968], Beaver [1968], Ohlson [1980]. The most popular one is the Altman Z-score model, which is frequently used in practice.

Estimating the probability of bankruptcy using the Altman Z-score: According to Jackson and Wood [2013], the five most popular techniques to predict the probability of bankruptcy are: (1) the Multiple Discriminant Analysis (MDA), (2) the logit model, (3) neural networks, (4) contingent claims and (5) univariate analysis.

Among MDA techniques, the Z-score is one of the most popular scoring tools for companies and organizations. It was developed in the late 60s [Altman, 1968, Beaver, 1968] and used since then to measure the financial health of a company or an organization. One of the primary applications of the Z-score is to predict bankruptcy. The probability p of bankruptcy can be estimated with a logistic function (see, e.g. Hillegeist et al. [2004], Kallunki and Pyykkö [2013]):

$$p = \frac{e^{-Z}}{1 + e^{-Z}}. \tag{3.23}$$

where Z is the value of Altman's Z-score .

The general form of the Z-score is the weighted sum of several financial attributes such as ratios, categorical or qualitative variables:

$$Z = \delta + \lambda_1\, \theta_1 + \lambda_2\, \theta_2 + \cdots + \lambda_n\, \theta_n,$$

where the θ_j are financial attributes, the λ_j values are positive coefficients and δ is a constant value. A higher score is a sign of a healthy financial situation. The Z-score values determine three areas: a low probability of default, a very risky area, and, in between, a gray area that contains companies with a moderate probability of bankruptcy.

The Z-score is widely recognized as a simple, applicable and consistent measure of the probability of failure. It has been confronted with the reality on numerous occasions. In 1968, the first model was based on the analysis of ratios on a sample of 66 industrial companies. The last large-scale tests carried out at the end of the 1990s showed a reliability of 94%. The original Z-score model was applicable only for public firms. The model was later modified in order to extend its application to both public and private firms and organizations [Altman, 2002]. The following Z-score formula is then proposed for private manufacturing companies:

$$Z = 0.717\theta_1 + 0.847\theta_2 + 3.107\theta_3 + 0.420\theta_4 + 0.998\theta_5,$$

where θ_1 is the *working capital/total assets* ratio, θ_2 is the *retained earnings/total assets* ratio, θ_3 is the *EBIT/total assets* ratio, θ_4 is the *book value of equity/book value of total liabilities* ratio and θ_5 is the *sales/total assets* ratio. The following equations detail the calculation of above ratios.

The *total assets*, denoted TA_t, include the cash at period $t \in \mathcal{T}$ and the sum of net assets values associated with all facilities.

$$TA_t = Cash_t + \sum_{t' \leq t} (\sum_{j \in \mathcal{J}} (O_j(y_{jt} - y_{j,t-1}) - Dep_j\; y_{j,t-1})) \quad \forall t \in \mathcal{T}$$

The *retained earnings* at period t, denoted RE_t, are defined as the net income left over for the company after distributing the dividends to its shareholders. Therefore, RE_t is simply obtained using the following equation.

$$RE_t = RE_{t-1} + (1 - \delta)NOPAT_t \quad \forall t \in \mathcal{T}$$

The *book value of equity* at period t, denoted BE_t, equals the sum of the retained

earnings and the new cash provided by the shareholders.

$$BE_t = RE_t + EE_t \quad \forall t \in \mathcal{T}$$

The *book value of liabilities*, BL_t, is defined as the portion of long-term debts due to the bank at period $t \in \mathcal{T}$. It is formulated as follows.

$$BL_t = \sum_{t' \leq t} (borrow_{t'} - (repay_{t'} - interest_{t'})) \quad \forall t \in \mathcal{T}.$$

Finally, the *sales*, at period $t \in \mathcal{T}$, denoted by SL_t, are given by the total revenues associated with all the facilities.

$$SL_t = \sum_{j \in \mathcal{J}} r_{jt} \quad \forall t \in \mathcal{T}.$$

Among the Z-score attributes, note that the term θ_1 depends on the working capital, which management is at the tactical level. Therefore, we did not include this attribute in our calculations.

Thus, following the definition the Z-score at period T is calculated as follows:

$$Z = 0.847 \, \frac{RE_{|\mathcal{T}|}}{TA_{|\mathcal{T}|}} + 3.107 \, \frac{EBIT_{|\mathcal{T}|}}{TA_{|\mathcal{T}|}} + 0.420 \, \frac{BE_{|\mathcal{T}|}}{BL_{|\mathcal{T}|}} + 0.998 \, \frac{SL_{|\mathcal{T}|}}{TA_{|\mathcal{T}|}}. \tag{3.24}$$

The Z-score values of the above formula, which determine three zones of discrimination, are 1.23 and 2.9. In other words, a low probability of default (if $Z \geq 2.9$), a very risky area (if $Z \leq 1.23$) and a gray area (if $1.23 < Z < 2.9$).

BE_t	Book value of equity at period $t \in \mathcal{T}$	$[0, \infty[$
BL_t	Book value of liabilities at period $t \in \mathcal{T}$	$[0, \infty[$
RE_t	Retained Earnings at period $t \in \mathcal{T}$	$[0, \infty[$
SL_t	Amount of sales at period $t \in \mathcal{T}$	$[0, \infty[$
TA_t	Total assets at period $t \in \mathcal{T}$	$[0, \infty[$
Z	value of Z-score	$[0, \infty[$

Table 3.5 – Variables related to the Altman Z-score

Estimating the probability of bankruptcy using debt ratio Since the Altman Z-score method requires many costly linearization, we use a simpler measure of the prob-

ability of bankruptcy: a non-decreasing function of the firm's debt ratio. Later, in Chapter 4, we will compare the results obtained by both methods.

Generally, a company will go bankrupt at period $t \in \mathcal{T}$ if the market value of its assets falls below the value of debt at this period. The higher the debt threshold compared to the company's assets, the more difficult it will be for assets value to reach it. Thus, the probability of default increases with the debt ratio $loanBalance_T/(loanBalance_T + equity_T)$ at period T. It is defined as follows:

$$p = \left(\frac{loanBalance_T}{loanBalance_T + equity_T} \right)^{\beta}, \tag{3.23}$$

Where the value of parameter β depends on the volatility of the company's assets ($\beta > 1$). Moreover, we introduce the variables $equity_t$ that represented the value of the equity at period $t \in \mathcal{T}$. It is equal to the equity at time $t-1$ plus the retained earnings at time t plus the new cash provided by shareholders at time t.

$$equity_t = equity_{t-1} + (1-\delta)NOPAT_t + EE_t \quad \forall t \in \mathcal{T}. \tag{3.24}$$

To avoid financial distress in earlier periods, we consider an upper bound on the debt ratio, set by the constraints (3.25):

$$loanBalance_t \leq \zeta \ (cash_t + \sum_{j \in \mathcal{J}} \sum_{t' \leq t} (O_j(y_{jt'} - y_{j,t'-1}) - Dep_j \ y_{j,t'-1})) \quad \forall t \in \mathcal{T}. \tag{3.25}$$

where $0 < \zeta < 1$ is a known parameter used to control the debt level at any period and the remaining of the right-hand side represents the net value of the total assets at period $t \in T$.

The present value of tax shields is computed by discounting the annual interest amount $interest_t$ at the rate α, multiplied by the firm tax rate η. The company will receive the interest tax shields with a probability $1-p$ (i.e., if it is not bankrupted) and pay a bankruptcy cost $\gamma \ OGV$ with probability p.

The mathematical expression of FGV is thus given by

$$FGV = (1-p)\eta \sum_{t \in \mathcal{T} \cup \mathcal{T}'} \frac{interest_t}{(1+\alpha)^t} - p \ \gamma \ OGV. \tag{3.26}$$

Finally, APV is the sum of OGV and FGV:

$$\begin{aligned} APV &= (1-p\gamma)OGV + (1-p)\eta \left(\sum_{t \in \mathcal{T} \cup \mathcal{T}'} \frac{interest_t}{(1+\alpha)^t} \right) \\ &= (1-p\gamma)OGV + (1-p)\eta \left(\sum_{t \in \mathcal{T} \cup \mathcal{T}'} \frac{\alpha\ loanBalance_{t-1}}{(1+\alpha)^t} \right). \end{aligned} \tag{3.27}$$

From this equation, it is clear that the leverage has a mixed impact on APV. On the one hand, it has a negative impact through the bankruptcy risk (p) and, on the other hand, a positive one through the tax shield benefit (last term of the APV function).

K_E	Cost of equity
N	Reimbursement duration of the loan
α	Interest rate of the loan
β	Bankruptcy probability parameter
γ	Bankruptcy cost parameter
δ	Dividend payout ratio
η	Firm tax rate
ζ	Upper bound of debt ratio

Table 3.6 – Parameters related to finance

APV	Adjusted present value of the firm	$]-\infty, \infty[$
$borrow_t$	Amount borrowed at period $t \in \mathcal{T}$	$[0, \infty[$
$cash_t$	Cash level at period $t \in \mathcal{T}$	$]-\infty, \infty[$
EE_t	External equity at period $t \in \mathcal{T}$	$[0, \infty[$
$equity_t$	Amount of equity at period $t \in \mathcal{T}$	$[0, \infty[$
FGV	Financially generated value of the firm	$]-\infty, \infty[$
IE_t	Invested amount of internal equity at period $t \in \mathcal{T}$	$[0, \infty[$
$interest_t$	Interest of the loan at period $t \in \mathcal{T}$	$[0, \infty[$
$loanBalance_t$	Value of the loan balance at period $t \in \mathcal{T}$	$[0, \infty[$
$NOPAT_t$	Net operating profit after tax at period $t \in \mathcal{T}$	$]-\infty, \infty[$
p	Probability of bankruptcy	$[0, 1]$
$repay_t$	Repayment of the loan at period $t \in \mathcal{T}$	$[0, \infty[$

Table 3.7 – Variables related to finance

3.3 Model's resolution

The developed mathematical model in Section 3.2 contains a set of non-linear expressions. This section first explains different linearization procedures and then describes how to use them to linearize the given model.

3.3.1 Linearization procedures

In the proposed mathematical model, several constraints are non-linear due to the product of two decision variables. We first recall several well known linearization techniques and then explain how these techniques are applied to our model.

- **Linearization 1: product of a real and a binary variable**

  Let u and v be two real positive variables and b a binary variable. Given an upper bound U of variable u, the expression $v = bu$ can be linearized by:

$$
\begin{aligned}
& v \leq u \\
& v \geq u - U(1 - b) \\
& v \leq Ub \\
& v \geq 0
\end{aligned}
$$

- **Linearization 2: product of two continuous variables**

  There is no exact way to linearize a product of two continuous variables u and v. A well-known approximation technique consists in defining $z_1 = 0.5(u + v)$ and $z_2 = 0.5(u - v)$ and to replace the expression uv by the equivalent expression $z_1^2 - z_2^2$. Although non-linear, this expression can be approximated with piece-wise linear approximation techniques.

  Besides this approach, another way consists of representing the continuous variables as a set of binary variables. This approach approximate non-integer values by rounding them to the nearest integer value. In our model, the continuous variables represent large monetary values. The consequence of rounding down these variables to the nearest integer value is then negligible. Assuming that variable u is rounded down, we use a power-of-two decomposition to represent u as a set of binary variables b_i:

$$u = b_0 + 2b_1 + 4b_2 + 8b_3 + \cdots + 2^{\lfloor log_2 U \rfloor} b_{log_2 U},$$

where U is an upper bound of v. For example, the value $100 = 4 + 32 + 64$ can be represented by the vector (0,0,1,0,0,1,1).

The product uv can now be rewritten as follows:

$$uv = v \sum_{i=0}^{i=\lfloor log_2 U \rfloor} 2^i b_i.$$

It is a weighted sum of the terms vb_i, where v is a continuous variable and b_i an integer variable. Each of these terms can be linearized with Linearization 1.

- **Linearization 3 (Piece-wise linearization):**

  Consider a general non-linear function $f(u)$ of a single variable u, where $u \in [u_0, u_m]$.

  We consider intermediate values $u_1, \ldots, u_{m-1}$ and intervals of the form $[u_i, u_{i+1}]_{0 \leq i \leq m-1}$. Let λ_i be a vector of binary variables, where $\lambda_i = 1$ if and only if $u \in [u_i, u_{i+1}]$.

  We define a vector ξ of continuous variables such that

$$u = \sum_{i=0}^{m-1} \xi_i$$
$$\lambda_i u_i \leq \xi_i \leq \lambda_i u_{i+1}$$
$$\sum_{i=0}^{m-1} \lambda_i = 1.$$

  Only one value in vector ξ is strictly positive and its corresponds to the value u. Hence, the function $f(u)$ is approximated by selecting the appropriate interval and considering the piece-wise linear approximation of $f(u)$ in this interval:

$$f(u) = \sum_i \lambda_i f(u_i) + \sum_i \left((\xi_i - \lambda_i u_i) \, \frac{f(u_{i+1}) - f(u_i)}{u_{i+1} - u_i} \right).$$

  Since only one value of vectors λ and ξ is strictly positive, this expression reduces to

$$f(u) = \lambda_i f(u_i) + (\xi_i - u_i) \, \frac{f(u_{i+1}) - f(u_i)}{u_{i+1} - u_i}$$

  for some $0 \leq i \leq m - 1$.

3.3.2 Linearization of the OGV second term - equation (3.15)

The second term of the OGV formula (3.15) is non-linear due to product of continuous variables CF_{jT} and binary variables y_{jt}. This expression can be linearized with Linearization 1.

Since the cash flow variables CF_{jT} measure the cash flows of facility $j \in \mathcal{J}$ after period T, its maximal value corresponds to the case where all customers' demands are served by facility j. Hence, the upper bound U can be set to $\sum_{i \in \mathcal{I}} P_i \, d_{iT}$.

3.3.3 Linearization of constraints (3.22)

In constraints (3.22), the expression $Max(0, cash_{t-1})$ is non-linear due to the Max operator. We introduce the continuous variables $IEMAX_t$ and auxiliary binary variables w_t satisfying:

$$
\begin{aligned}
& IEMAX_t \geq cash_{t-1} && \forall t \in \mathcal{T} \\
& IEMAX_t \leq cash_{t-1} + U \, (1 - w_t) && \forall t \in \mathcal{T} \\
& IEMAX_t \leq U \, w_t && \forall t \in \mathcal{T} \\
& IEMAX_t \geq 0 && \forall t \in \mathcal{T},
\end{aligned}
$$

where $U = \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} P_i \, d_{it}$.

3.3.4 Linearization of the probability of bankruptcy p

We proposed two possible methods to estimate the probability of bankruptcy. Thus here we explain their linearization process separately.

3.3.4.1 Altman Z-score method

Integrating Altman Z-score in SCND models implies dealing with several non-linear mathematical expressions.

Z-score ratios The first non-linearities are due to the ratios included in the Z-score formula (equation (3.24)).

Let us consider the linearization of $\theta_2 = \frac{RE_T}{TA_T}$. The same principle applies to other ratios. First, using a power-of-two decomposition, TA_T can be represented by a set of

binary variables b_i. The fraction can then be rewritten as $\theta_2 = \frac{RE_T}{\sum_{j=0}^{j=U} 2^j b_j}$.

The above formula can be rewritten as $\theta_2 \times \sum_{j=0}^{j=U} 2^j b_j = RE_T$. This formulation does not contain any ratio. However, it multiplies the continuous variable θ_2 with a set of binary variables b_j.Thus, Linearization 1 can be used.

Note that the maximum possible value of U is considered as if all customers are satisfied at period T and all facilities are selected to operate. Therefore U is set to $\sum_{j \in J} O_j + \sum_{i \in I} P_i \, d_{iT}$

Probability of bankruptcy The second non-linearities result from calculation of probability of bankruptcy (equation 3.23). This formula is a concave function with respect to the value of z, and we approximated it through piece-wise linearization.

3.3.4.2 Debt ratio method

In equation (3.23), the probability of bankruptcy is given by $p = \left(\frac{loanBalance_T}{loanBalance_T + equity_T}\right)^{\beta}$.

We consider the debt ratio $\rho = \frac{loanBalance_T}{loanBalance_T + equity_T}$. This ratio can be linearized similar to the linearization of equation (3.24). After linearizing the ratio, we obtain the expression $p(\rho) = \rho^{\beta}$, which can be linearized using a piece-wise linearization.

3.3.5 Linearization of the tax shield benefit - First term in equation (3.26)

The tax shield benefit is calculated as $(1-p)\ \eta \sum_{t \in \mathcal{T} \cup \mathcal{T}'} \frac{interest_t}{(1+\alpha)^t}$, where p and $interest_t$ are continuous variables. We use Linearization 2. Here U can be set to the maximum interest i.e., the interest paid if all candidate facilities are opened using debt financing. Ignoring the impact of the time value of money: $U = N \times \alpha \times \sum_{j \in J} O_j$

3.3.6 Linearization of the expected bankruptcy cost - second term in equation (3.26)

EBC is estimated as $p \times \gamma \times OGV$ where p and OGV are continuous variables. We use Linearization 2. The maximum value for OGV can be obtained if all customers are served at all periods without any cost. Thus $U = (1-\eta) \times \left(\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} P_i \, d_{it} + \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}'} P_i \, d_{iT} \right)$

3.4 Illustrative example

To illustrate how both logistic and financial components influence SCND decisions, we propose a small example with two periods, two candidate facilities A and B and one single customer. As represented in Figure 3.4, the customer's demand in both periods is 3000 units. The distance between the customer and facilities A and B is 1000 and 500, respectively. Figure 3.4 gives the production capacity as well as the fixed opening cost and the unitary processing cost of both candidate facilities

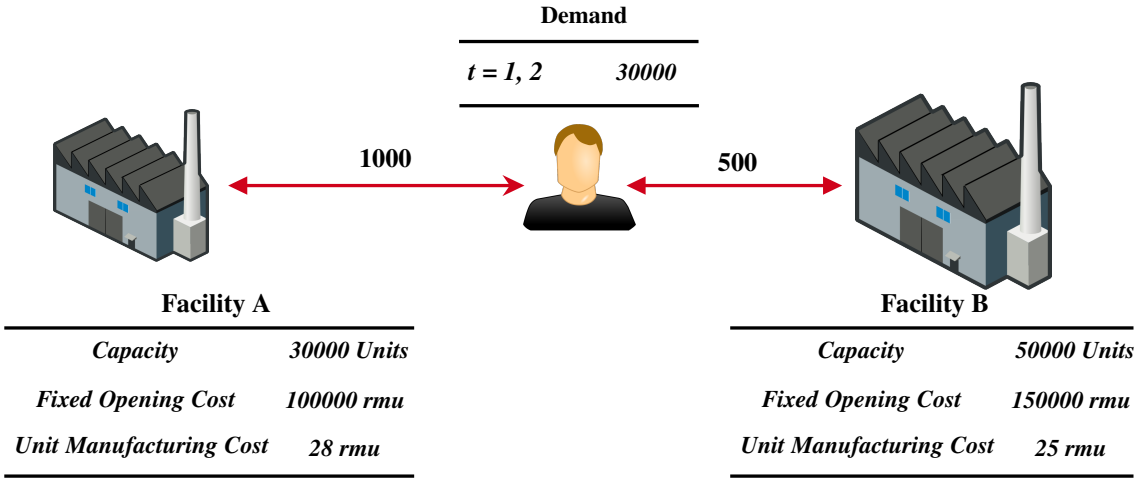

Figure 3.4 – A small example with one customer and two candidate facilities

The fictitious monetary unit used in this example is called *relative money unit* (*rmu*). The reimbursement duration is 15 years and the interest rate 5%. Table 3.8 lists all other parameters used in this example.

Product Selling Price	80 *rmu*
Unit Transportation Cost	0.02 *rmu* / km
Fixed yearly running cost	10% of opening cost / year
Salvage value of facilities	0 *rmu*
Life time of facilities	10 years
Tax Rate	40%
Cost of Equity	10%
Dividend rate	30%
Bankruptcy cost parameter γ	0.5

Table 3.8 – Parameters used in the example

Given these data, we run the mathematical model presented in this chapter, by forcing

the selection of Facility A, and then the selection of candidate B. For each of the two solutions obtained, the first three lines of Table 3.9 show the OGV, FGV and APV values. The following lines detail the value of the processing costs, transportation costs and fixed yearly running costs as well as relevant financial indicators: the debt ratio, the probability of bankruptcy, the estimated bankruptcy cost, and the value of the tax shield benefit. Note that to estimate the probability of bankruptcy, we used the debt ratio method in this example.

Objective Function	Decision	
	Facility A	Facility B
OGV	**12363**	9173
FGV	8666	**13054**
APV	21029	**22227**
Processing cost	168000	150000
Transportation cost	120000	60000
Fixed yearly running cost	20000	30000
Debt ratio	38%	40%
Probability of bankruptcy	2.28%	2.57%
Expected bankruptcy cost	141	118
Tax shield benefit	8807	13172

Table 3.9 – Results of the example for each objective function

These results show how integrating financial decisions into the logistic decisions can alter the network design. Maximizing the value associated with logistic decisions, i.e., OGV, results in opening facility A, while maximizing the value associated with both the logistic and financial decisions (APV = OGV + FGV) leads to open facility B. Comparing the APV values, opening facility B increases the firm's value by around 5%. We observe that the probability of bankruptcy is roughly the same in both scenarios. Facility B benefits from a large value of tax shield benefit and small transportation costs. This illustrates that the choice of facility B results from a trade-off between financial and logistic considerations.

3.5 Conclusion

In this chapter, we adapted the Adjusted Present Value (APV) as the objective function in SCND models. This objective function integrates both the traditional logistic costs that

are already part of the OGV (i.e., NPV) and additional costs related to debt or equity financing. To estimate the probability of bankruptcy (a part of FGV), two methods were described: The Altman Z-score method, and, the debt ratio method. As the presented model contains some non-linear expressions, we proposed a set of linearization procedures, such that it is formulated as an MILP model. Finally, we showed how integrating financial and logistic decisions influence the SCND configuration through an illustrative example. In the following chapter, we conduct a set of computational results to evaluate and analyze the presented model.

Chapter 4

Numerical Experiments

In this chapter, we describe the numerical experiments that were performed to evaluate the performance of the model proposed in Chapter 3. We did not find any related benchmark instance that could be used to validate and experiment this model. Thus, new instances were generated, following generation rules used by various authors. The procedure used to generate these instances is explained in section 4.1. Section 4.2 proposes two solution approaches, called *Integrated Approach* and *Sequential Approach*, to solve the mathematical model. Section 4.3 first compares two methods to estimate the probability of bankruptcy (described in Chapter 3), then details the numerical results obtained by solving the generated instances using the IBM Cplex solver. Section 4.4 summarizes the findings of the numerical experiments and concludes.

4.1 Data generation

We generated instances that mimic a supply chain network with several markets, each market having its own costs, product prices, etc. We considered different numbers of customers, from 60 to 480 with a step of 30. Following Cordeau et al. [2006a], the number $|\mathcal{J}|$ of candidate facilities is defined as 10% of the number of customers. The maximum number of open facilities ($\mathcal{J}_{max}$) is defined as $\lceil 0.5|\mathcal{J}| \rceil$. In all instances, $|\mathcal{T}| = 5$ and $|\mathcal{T}'| = 10$ time periods were considered. The next subsections detail the steps followed by the data generation. Note that in the remainder of this article, all costs/prices are expressed in a fictitious monetary unit called *relative money unit* (*rmu*).

4.1.1 Logistic data and parameters

All customers and candidate facility locations were generated in a 1000×1000 grid. Both axes of the grid are decomposed into 5 intervals of size 200. We thus defined 25 squared areas called *regions*. The following paragraphs detail the principles of the data generation

in this grid.

Markets The grid is divided into several markets (from 2 to 5), where a market is a connected set of regions. For each market, we first generated a general *economic index* that is used as a proxy to indicate the economic situation of the market and generate the costs and prices in accordance. The economic indices are generated with a uniform distribution between 50 and 150, and the higher the economic index, the higher the market's costs and prices.

Customers and candidate facilities To generate the location of customers and candidate facilities, the two following patterns were implemented:

- **Random:** The coordinates of the customers and facilities are generated randomly with a uniform distribution over the entire grid.
- **Clustered:** Following Eskandarpour et al. [2017], 4 or 5 regions are chosen randomly to form clusters (the choice between 4 or 5 is random). Then, around 60% of customers (resp. candidate facilities) are located in the chosen regions; and the remaining 40% are located randomly with a uniform distribution all over the grid.

Customers' demand In order to evaluate various practical situations, two different demand patterns are considered.

- **Random**: Following Yeh [2006], the customer demands at each period are generated with a uniform distribution in the interval [100, 300].
- **Growing**: The demand of each customer still lies in the interval [100, 300], with the additional property that the total demand grows by a factor in the interval [1.05, 1.25] between two successive periods. Note that with this demand pattern, the total demand is growing but the individual demand of some customers may decrease between two successive periods.

Capacity of the facilities Each candidate location has a given capacity. We have generated three sizes of facilities, named *small*, *medium* and *large*, representing 80%, 100% and 130% of the ratio D/J_{max} respectively, where D is the average demand per period. The capacity of each facility is randomly chosen such that about 1/3 of facilities are small, 1/3 are medium and 1/3 are large.

Logistic costs Processing costs, fixed costs of facilities and selling prices are defined according to an *economic index* generated with a uniform distribution between values 50 and 150. The range $[50, 150]$ is decomposed into 5 intervals, and for each interval, the costs and the selling price are generated according to a uniform distribution as detailed in Table 4.1 (lines 2, 3 and 4).

Economic index	[50, 70[	[70, 90[	[90, 110[	[110, 130[	[130, 150]
Processing cost μ $(rmu/unit)$	[1, 1.1]	[1.1, 1.2]	[1.2, 1.3]	[1.3, 1.4]	[1.4,1.5]
Opening cost parameter φ	[625, 650]	[650, 675]	[675, 700]	[700, 725]	[725, 750]
Selling price P $(rmu/unit)$	[3,3.4]	[3.4, 3.8]	[3.8, 4.2]	[4.2, 4.6]	[4.6, 5]

Table 4.1 – Generation of logistic costs

- **Processing cost:** Processing cost (μ_j) of small-sized facilities is defined randomly with a uniform distribution on an interval depending on the economic index of the market where facility j lies.

  To model economies of scale, the processing cost at average-sized facilities and large-sized facilities is obtained by multiplying these values by 0.98 and 0.96, respectively. These parameters, listed in Table 4.1, have been empirically set in such a way that the relative part of processing costs roughly represents around $35\% - 45\%$ of the total costs in each instance.

- **Fixed opening cost:** The value of the fixed opening cost (O_j) is strongly related to the value of the real estate and to the facility's capacity. To model economies of scale as the capacity grows, we assume that the fixed opening cost of a facility j is roughly proportional to the square root of its capacity. We set $O_j = \varphi_j \sqrt{Capa_j}$, where $Capa_j$ represents the capacity of facility j and φ_j is the opening cost parameter at location j (mainly determined by the cost of the local real estate and salaries). The value of φ_j is generated randomly with a uniform distribution between 625 and 750. See the details in Table 4.1.

  These intervals have been empirically set in such a way that the relative part of the fixed opening costs roughly represent $25\% - 35\%$ of the total logistics costs (see, e.g. Eskandarpour et al. [2017] for a similar approach).

- **Fixed yearly running cost:** the fixed yearly running cost (F_j) is set at 5% of the fixed opening cost of each facility, O_j, per year. Thus, it represents around $10\% - 15\%$

of the total costs.

- **Transportation cost:** transportation costs are considered proportional to the Euclidean distance traveled. We also consider that transportation costs are similar in all markets. To obtain a transportation cost representing 10% to 20% of total costs, the unit transportation cost, ω, is set at 0.002 rmu in all the instances.

Selling price The price P_i proposed to customer $i \in \mathcal{I}$ depends on the market in which i lies. Its value is included in the interval $[3, 5]$. See the detailed values in Table 4.1

Accessibility parameters The accessibility parameter V_{ij} is set to value 1 if the distance between facility $j \in \mathcal{J}$ and customer $i \in \mathcal{I}$ is less than or equal to 750 (roughly half of the longest possible distance in the grid), and 0 otherwise.

4.1.2 Financial parameters

Following a recent KPMG study [Castedello and Schöniger, 2019], the average cost of debt α and the average cost of equity K_E are set at 3% and 9%, respectively. We consider a lifetime L_j equal to 10 years, a depreciation Dep_j calculated with this lifetime value, and a negligible salvage value SV_j [Laínez et al., 2007]. The value of the bankruptcy cost parameter γ is set to 0.5 and the upper bound of the debt ratio ζ is set to 0.7 in order to ensure an acceptable financial situation. The value of bankruptcy probability parameter β in constraint (3.23) is set at 4. The corporate tax rate η is set at 30%.

4.1.3 Set of instances

Following the principles described above, 60 instances were generated: 30 instances with random locations and 30 instances with clustered locations; in each group, 15 instances with random demand and 15 instances with growing demand.

The instance names are of the form "$|\mathcal{I}|$-X-Y", where $|\mathcal{I}|$ is the number of customers, $X \in \{R, C\}$ is the type of geographical distribution (R=random, C=clustered) and $Y \in \{R, G\}$ is the type of demand (R=random, G=growing). For example, the instance 60-R-G has 60 randomly located customers with a growing demand profile.

4.2 Integrated and Sequential approaches

To solve the mathematical model of Chapter 3, two solution approaches are proposed. As represented in Figure 3.1, APV can be decomposed into a logistic part (OGV) and a financial part (FGV). Therefore, the mathematical model can be decomposed into two sub-problems: a *logistic sub-problem*, which determines which facilities should be opened, which customers should be served, as well as the associated product flows, and a *financial sub-problem*, which optimizes the financial decisions and the cash flows.

While OGV calculation can be performed independently of FGV, the converse is not true. This is why we implemented two approaches, called *Integrated Approach* and *Sequential Approach*, to assess the impact of financial decisions on the SCND problem. These approaches are depicted in Figure 4.1.

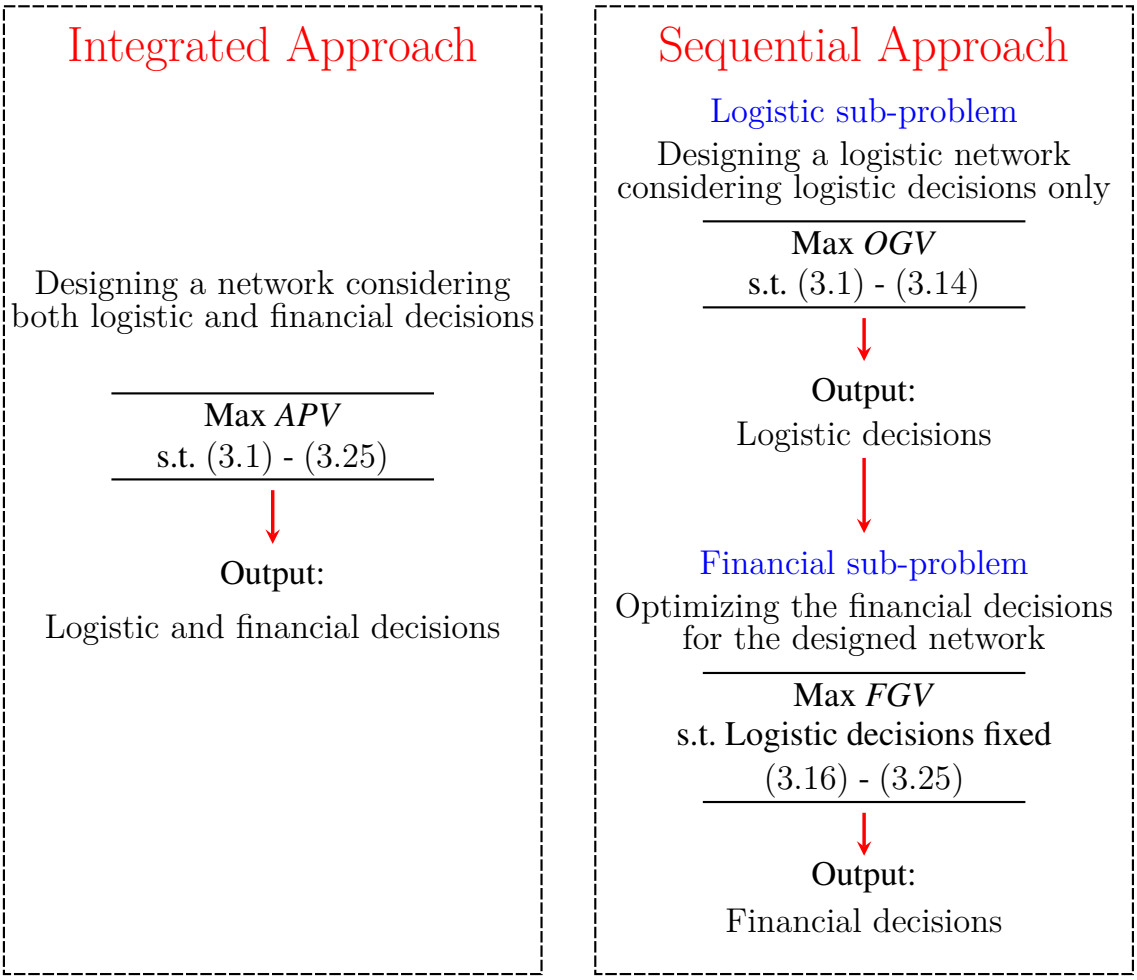

Figure 4.1 – Integrated Approach vs. Sequential Approach

The Integrated Approach considers the whole mathematical model (3.1)–(3.27) at once and maximizes APV by simultaneously determining the value of all logistic and financial variables.

In the Sequential Approach, the logistic sub-problem and the financial sub-problem are solved sequentially. First the OGV formula defined by equation (3.15) is maximized, subject to the constraints (3.1)—(3.14). Then, once the variables related to the logistic sub-problem have been determined, the *OGV* is a constant value. Hence, maximizing FGV amounts to maximizing the APV formula defined in constraint (3.27), subject to constraints (3.16)—(3.25). Obviously, implementing a symmetric sequential approach (financial decision first, then logistics decision) is not relevant in our case, since the financial consequence depend on logistic decisions.

Type of	Constraints			Binary Variables			Continuous Variables		
Instance	Total	Log.c	Fin.l	Total	Log.	Fin.l	Total	Log.	Fin.
60	3 397	3 155	242	536	455	80	2 564	2 341	223
90	5 557	5 282	275	774	684	90	5 387	5 131	256
120	8 797	8 489	308	1 012	912	100	9 290	9 001	289
150	13 117	12 776	341	1 250	1 140	110	14 273	13 951	322
180	18 517	18 143	374	1 488	1 368	120	20 336	19 981	355
210	24 997	24 590	407	1 726	1 596	130	27 479	27 091	388
240	32 557	32 117	440	1 964	1 824	140	35 702	35 281	421
270	41 197	40 724	473	2 202	2 052	150	45 005	44 551	454
300	50 917	50 411	506	2 440	2 280	160	55 388	54 901	487
330	61 717	61 178	539	2 678	2 508	170	66 851	66 331	520
360	73 597	73 025	572	2 916	2 736	180	79 394	78 841	553
390	86 557	85 952	605	3 154	2 964	190	93 017	92 431	586
420	100 597	99 959	638	3 392	3 192	200	107 720	107 101	619
450	115 717	115 046	671	3 630	3 420	210	123 503	122 851	652
480	131 917	131 213	704	3 868	3 648	220	140 366	139 681	685

Table 4.2 – Number of constraints and variables of the model

Table 4.2 enumerates, for each size of instance, the number of binary and continuous variables as well as the number of constraints in the mathematical model. The table details this information for the integrated model and for the logistic (log.) and financial (fin.) parts used in the sequential approach. Note that the binary variables in the financial part of the model come only form the linearization of nonlinear constraints.

4.3 Numerical experiments

All numerical experiments were run on an Intel(R) Xeon(R) Gold 6230 CPU @ 2.10GHz using single core. The mathematical model was solved with the IBM ILOG CPLEX Optimization Studio 20.1.0 solver, with a time limit of 21 600 seconds (6 hours).

4.3.1 Assessment of estimating the probability of bankruptcy

As discussed in Chapter 3, we proposed two possible methods to estimate the probability of bankruptcy: the Altman Z-score estimation and the debt ratio estimation. To evaluate these methods, we draw a comparison by solving 4 different instances, using one of the methods to calculate the probability of bankruptcy, and to calculate the same probability a posteriori with the other method. We report the results of four instances in Table 4.3.

For example, for the instance 60-C-G, we first solve it with the Altman Z-score method. In the obtained solution, the value of Z-score equals 4.20, thus the corresponding probability of bankruptcy equals: $p = \frac{e^{-4.20}}{1+e^{-4.20}} \approx 1.48\%$. Then, the debt ratio is calculated a posteriori which equals 49%.

Second, we solve the same instance with the debt ratio method. The debt ratio of the obtained solution is 0.45%, thus the corresponding probability of bankruptcy equals: $p = 0.45^4 \approx 4.00\%$. The Z-score is then calculated which equals 4.38.

As noted in Table 4.3, the probability of bankruptcy obtained by the Altman Z-score is always considerably lower than the debt ratio method. Consequently, the capital structure of these solutions is mainly made up of debt (which is not realistic). While the higher probability of bankruptcy with the debt ratio method prevents the model from using only debt for the investments. The debt ratio method tends to employ both equity and debt, which is closer to the practical sense of firms' capital structure.

Thus, to model the bankruptcy prediction more realistically, we end up the model with the debt ratio method. Hence, the following numerical experiments are all conducted using that method.

Instance	Estimation Method for the Probability of Bankruptcy	Z-Score	Debt Ratio (%)	Probability Bankruptcy (%)
60-C-G	Altman Z-score	4.20	49	1.48
	Debt Ratio	4.38	45	4.00
120-R-R	Altman Z-score	4.58	50	1.02
	Debt Ratio	4.63	43	3.30
150-C-G	Altman Z-score	4.75	49	0.78
	Debt Ratio	4.81	40	2.50
210-R-R	Altman Z-score	4.31	48	1.33
	Debt Ratio	4.35	44	3.80

Table 4.3 – Comparing the Altman Z-score and the debt ratio methods for estimating the probability of bankruptcy

4.3.2 Assessment of the sequential and integrated approaches

Table 4.4 compares the computational time needed to solve the integrated and the sequential approaches, respectively. Columns 2 and 4 indicate the computational time (in seconds) to get an optimal solution. Columns 3 and 5 indicate the optimality gap when such a solution could not be reached after 6 hours of computation.

This table first shows that our proposed model is tractable for realistic size instances. As it could be expected, the sequential approach is easier to solve than the integrated approach (the computational time is smaller for the sequential approach): up to 300 customers, all instances could be solved to the optimality within 6 hours except for 10 instances which have small optimality gap. Also the highest gap with this approach is 10.00% (instance 450-C-G). With the integrated approach, within 6 hours, the solver can either solve instances of up to 240 customers to the optimality or find solutions with small optimality gaps. Also, the highest gap with this approach is 36.87% (instance 420-C-G). This table suggests that specific solution methods (either exact or heuristics) should be used for larger instances.

Apart from the solution approach, Table 4.4 denotes another meaningful pattern between the instances. Roughly speaking, the instances with the growing demand profile are more difficult to solve by the solver. In the same problem set: *a.* for the instances solved to the optimality, those with the growing demand take more CPU time than others; *b.* among the instances that could not be solved to optimality, the optimality gap is higher with a growing demand. Interpreting the reason behind that needs a detailed solution for each instance. This will be developed in Section 4.3.3.

	Integrated		Sequential	
Instance	CPU (in s)	Gap	CPU (in s)	Gap
60-R-R	1 101		1 097	
60-R-G	1 810		1 340	
60-C-R	1 502		1 347	
60-C-G	3 575		2 595	
90-R-R	2 391		2 473	
90-R-G	5 783		3 155	
90-C-R	3 108		2 023	
90-C-G	21 600	*0.02%*	3 132	
120-R-R	13 726		12 848	
120-R-G	21 600	*0.03%*	4 086	
120-C-R	21 600	*0.02%*	8 231	
120-C-G	21 512		10 856	
150-R-R	18 851		3 796	
150-R-G	21 600	*0.02%*	9 375	
150-C-R	5 094		5 032	
150-C-G	21 600	*0.01%*	10 569	
180-R-R	21 600	*0.02%*	11 015	
180-R-G	21 600	*0.02%*	14 452	
180-C-R	21 600	*0.03%*	21 600	*0.04%*
180-C-G	19 089		15 342	
210-R-R	21 600	*0.04%*	21 600	*0.02%*
210-R-G	21 600	*0.01%*	18 030	
210-C-R	21 600	*0.10%*	21 600	*0.08%*
210-C-G	21 600	*0.06%*	21 600	*0.03%*
240-R-R	21 600	*0.05%*	9 255	
240-R-G	21 600	*0.05%*	21 501	
240-C-R	15 482		21 600	*0.05%*
240-C-G	21 600	*0.49%*	21 600	*0.03%*

Table 4.4 – Comparison of CPU times and optimality gaps of the sequential and the integrated approaches - 1^{st} part

	Integrated		Sequential	
Instance	CPU (in s)	Gap	CPU (in s)	Gap
270-R-R	21 600	*0.18%*	12 384	
270-R-G	21 600	*4.54%*	21 600	*0.04%*
270-C-R	18 627		7 304	
270-C-G	17 922		13 752	
300-R-R	21 600	*0.15%*	21 600	*0.01%*
300-R-G	21 600	*3.53%*	21 600	*0.56%*
300-C-R	21 600	*0.87%*	16 208	
300-C-G	21 600	*6.52%*	21 600	*0.03%*
330-R-R	21 600	*2.81%*	20 129	
330-R-G	21 600	*7.49%*	21 600	*0.03%*
330-C-R	21 600	*4.73%*	21 600	*0.02%*
330-C-G	21 600	*9.67%*	21 600	*2.18%*
360-R-R	21 600	*1.85%*	21 600	*0.03%*
360-R-G	21 600	*6.38%*	21 600	*1.33%*
360-C-R	21 600	*2.30%*	12 756	
360-C-G	21 600	*6.84%*	21 600	*1.85%*
390-R-R	21 600	*3.16%*	7 118	
390-R-G	21 600	*15.45%*	21 600	*3.66%*
390-C-R	21 600	*4.01%*	21 600	*0.18%*
390-C-G	21 600	*20.19%*	21 600	*2.50%*
420-R-R	21 600	*11.79%*	21 600	*1.47%*
420-R-G	21 600	*33.95%*	21 600	*9.40%*
420-C-R	21 600	*12.02%*	21 600	*0.08%*
420-C-G	21 600	*36.87%*	21 600	*3.68%*
450-R-R	21 600	*6.30%*	21 600	*0.12%*
450-R-G	21 600	*31.97%*	21 600	*4.32%*
450-C-R	21 600	*11.32%*	21 600	*4.08%*
450-C-G	21 600	*28.88%*	21 600	*10.00%*
480-R-R	21 600	*8.22%*	18 967	
480-R-G	21 600	*17.44%*	21 600	*1.51%*
480-C-R	21 600	*20.13%*	21 600	*1.13%*
480-C-G	21 600	*27.10%*	21 600	*2.72%*

Table 4.4 – Comparison of CPU times and optimality gaps of the sequential and the integrated approaches - 2^{nd} part

The performance of these two approaches is evaluated using five indicators. Table 4.5 reports their value for each instance.

Instance	Approach	APV (rmu)		Fill rate (%)	ROE (%)	ROA (%)	Leverage ratio (%)
60-R-R	Integrated	38 052	*+0.63%*	87	16.13	8.12	35.32
	Sequential	37 816		76	18.89	10.49	33.68
60-R-G	Integrated	40 609	*+0.12%*	81	15.44	8.38	28.83
	Sequential	40 562		76	18.15	8.92	30.17
60-C-R	Integrated	43 227	*+0.88%*	87	19.71	10.76	33.86
	Sequential	42 848		61	21.56	10.97	33.77
60-C-G	Integrated	44 610	*+1.58%*	80	20.17	9.27	30.19
	Sequential	43 914		60	19.91	10.17	28.65
90-R-R	Integrated	42 421	*+2.40%*	95	16.73	8.41	34.13
	Sequential	41 428		73	18.21	9.20	32.94
90-R-G	Integrated	46 225	*+0.56%*	85	15.59	8.24	30.41
	Sequential	45 969		74	17.22	8.74	31.92
90-C-R	Integrated	53 776	*+0.00%*	67	17.83	9.14	27.80
	Sequential	53 776		67	17.83	9.14	27.80
90-C-G	Integrated	56 992	*+0.00%*	60	21.40	9.34	31.13
	Sequential	55 992		60	21.40	9.34	31.13
120-R-R	Integrated	67 050	*+0.22%*	86	16.79	8.32	28.74
	Sequential	66 909		81	16.87	8.45	29.31
120-R-G	Integrated	67 976	*+0.00%*	82	18.85	8.87	30.87
	Sequential	67 976		82	18.85	8.87	30.87
120-C-R	Integrated	52 554	*+1.18%*	74	16.36	7.68	36.48
	Sequential	51 943		58	19.62	9.56	34.74
120-C-G	Integrated	54 550	*+2.60%*	83	17.59	8.27	30.77
	Sequential	53 168		64	20.71	9.18	31.28

Table 4.5 – Performance comparison of the sequential and integrated approaches - 1^{st} part

The first indicator (column 3) is the APV. Since the APV is the objective function to be maximized in the integrated approach, the results of this approach are generally better than or equivalent to those of the sequential approach—when the instances could be solved to optimality or near optimality with the integrated approach. Among the first 40 instances (up to 330 customers), 26 have better APV, 9 are equivalent, while 5 are worst with the integrated approach due to a significant optimality gap. The last 20 instances with the integrated approach also have mostly significant optimality gaps; thus, their APV is generally worst than the APV of the sequential approach.

Instance	Approach	APV (rmu)		Fill Rate (%)	ROE (%)	ROA (%)	Leverage ratio (%)
150-R-R	Integrated	182 715	*+0.56%*	95	21.52	10.20	26.13
	Sequential	181 700		84	22.84	10.96	26.09
150-R-G	Integrated	175 516	*+0.37%*	91	24.74	10.93	27.83
	Sequential	174 873		86	24.45	11.20	26.79
150-C-R	Integrated	150 743	*+0.68%*	97	18.36	9.12	26.84
	Sequential	149 719		87	19.60	9.67	27.02
150-C-G	Integrated	143 955	*+0.00%*	89	20.56	9.87	27.65
	Sequential	143 955		89	20.56	9.87	27.65
180-R-R	Integrated	121 294	*+0.00%*	82	16.60	8.51	26.49
	Sequential	121 294		82	16.60	8.51	26.49
180-R-G	Integrated	122 141	*+0.27%*	94	17.04	8.65	28.43
	Sequential	121 816		85	18.78	9.07	29.58
180-C-R	Integrated	132 608	*+0.43%*	87	17.02	8.53	26.90
	Sequential	132 034		84	17.22	8.65	26.38
180-C-G	Integrated	129 500	*+0.00%*	85	19.45	9.12	29.25
	Sequential	129 500		85	19.45	9.12	29.25
210-R-R	Integrated	139 675	*+0.63%*	84	17.80	8.63	30.03
	Sequential	138 804		77	17.70	8.80	29.32
210-R-G	Integrated	135 940	*+0.94%*	89	17.11	8.58	29.68
	Sequential	134 673		77	18.33	9.01	29.97
210-C-R	Integrated	148 538	*+0.60%*	80	18.20	8.90	29.17
	Sequential	147 655		76	17.90	8.98	28.37
210-C-G	Integrated	145 133	*+0.35%*	83	19.04	9.06	30.32
	Sequential	144 626		78	18.94	9.23	29.91
240-R-R	Integrated	190 433	*−0.01%*	94	12.37	7.82	21.86
	Sequential	190 451		94	15.86	7.98	27.06
240-R-G	Integrated	162 316	*+0.00%*	94	15.71	8.40	27.12
	Sequential	162 316		94	16.83	8.55	28.04
240-C-R	Integrated	188 954	*+0.00%*	94	16.26	8.26	27.14
	Sequential	188 954		94	16.26	8.26	27.14
240-C-G	Integrated	165 440	*+0.07%*	97	16.87	8.51	27.79
	Sequential	165 321		95	16.94	8.57	27.84

Table 4.5 – Performance comparison of the sequential and integrated approaches - 2^{nd} part

Instance	Approach	APV (rmu)		Fill Rate (%)	ROE (%)	ROA (%)	Leverage ratio (%)
270-R-R	Integrated	141 044	*+0.51%*	72	16.59	8.39	27.86
	Sequential	140 339		69	16.51	8.44	26.39
270-R-G	Integrated	151 717	*−0.14%*	74	17.72	8.77	28.94
	Sequential	151 932		74	18.66	9.23	28.59
270-C-R	Integrated	251 230	*+0.42%*	83	20.02	9.80	26.21
	Sequential	250 175		74	21.31	10.26	26.50
270-C-G	Integrated	266 056	*+0.13%*	86	21.01	10.07	27.01
	Sequential	265 698		81	22.34	10.43	27.66
300-R-R	Integrated	199 527	*+0.00%*	94	17.96	9.07	28.74
	Sequential	199 563		94	17.96	9.07	28.74
300-R-G	Integrated	190 850	*+0.05%*	96	17.64	8.83	28.45
	Sequential	190 764		96	18.33	8.94	28.74
300-C-R	Integrated	157 033	*+0.21%*	91	15.67	7.82	28.42
	Sequential	156 706		86	15.40	7.90	27.14
300-C-G	Integrated	154 220	*−0.14%*	92	16.17	8.28	28.45
	Sequential	154 434		92	16.45	8.33	29.08
330-R-R	Integrated	151 691	*−0.12%*	88	15.30	7.81	27.10
	Sequential	151 874		80	15.80	8.09	27.64
330-R-G	Integrated	145 356	*+0.35%*	87	17.02	8.32	29.91
	Sequential	144 842		82	16.80	8.44	28.84
330-C-R	Integrated	132 078	*+1.26%*	87	14.52	7.49	28.66
	Sequential	130 440		78	14.83	7.68	27.76
330-C-G	Integrated	122 932	*−0.09%*	82	15.79	7.88	29.94
	Sequential	123 046		79	16.10	8.04	29.97
360-R-R	Integrated	240 185	*−0.12%*	93	17.68	8.97	28.96
	Sequential	240 472		92	17.92	9.02	29.15
360-R-G	Integrated	238 779	*−0.80%*	95	17.68	8.72	26.71
	Sequential	240 698		95	18.01	8.77	27.36
360-C-R	Integrated	227 779	*−0.06%*	95	17.21	8.81	28.95
	Sequential	227 912		95	17.21	8.81	28.95
360-C-G	Integrated	227 158	*−0.05%*	96	17.32	8.65	27.82
	Sequential	227 265		98	17.38	8.74	27.32

Table 4.5 – Performance comparison of the sequential and integrated approaches - 3^{rd} part

Instance	Approach	APV (rmu)		Fill Rate (%)	ROE (%)	ROA (%)	Leverage ratio (%)
390-R-R	Integrated	295 032	*−0.04%*	93	17.70	8.93	26.29
	Sequential	295 144		91	17.79	8.99	26.32
390-R-G	Integrated	284 489	*−1.21%*	91	18.06	9.13	25.70
	Sequential	287 927		96	18.72	9.26	26.43
390-C-R	Integrated	231 785	*−0.13%*	96	15.95	8.13	27.15
	Sequential	232 092		91	18.24	9.41	31.13
390-C-G	Integrated	220 495	*−2.37%*	93	17.34	8.63	28.42
	Sequential	225 718		92	17.77	8.75	29.12
420-R-R	Integrated	137 262	*−3.43%*	78	14.99	7.60	28.59
	Sequential	141 971		67	15.47	7.88	28.01
420-R-G	Integrated	130 963	*−7.31%*	83	16.57	8.24	30.87
	Sequential	140 537		66	17.37	8.56	31.12
420-C-R	Integrated	109 296	*−2.56%*	53	15.97	7.95	28.50
	Sequential	112 092		39	16.67	8.55	26.50
420-C-G	Integrated	102 362	*−6.44%*	62	17.79	8.71	30.70
	Sequential	108 951		40	19.21	9.17	29.96
450-R-R	Integrated	293 924	*−1.81%*	82	18.11	9.33	25.21
	Sequential	299 233		82	18.53	9.43	26.85
450-R-G	Integrated	285 797	*−11.91%*	86	20.28	9.70	29.22
	Sequential	289 627		89	18.95	9.32	26.91
450-C-R	Integrated	237 270	*−3.23%*	69	19.77	9.49	28.54
	Sequential	244 935		66	19.40	9.56	28.08
450-C-G	Integrated	227 004	*−2.13%*	74	18.64	9.31	25.78
	Sequential	231 835		66	20.16	9.72	29.75
480-R-R	Integrated	292 594	*−1.91%*	91	15.68	8.20	25.13
	Sequential	298 191		95	16.02	8.25	26.89
480-R-G	Integrated	281 687	*−3.93%*	99	17.08	8.48	29.84
	Sequential	292 765		98	16.61	8.55	26.82
480-C-R	Integrated	226 565	*−7.68%*	92	14.60	7.63	26.73
	Sequential	243 956		93	14.72	7.63	26.89
480-C-G	Integrated	223 118	*−7.42%*	97	9.48	7.21	16.48
	Sequential	239 675		97	16.37	8.11	29.95

Table 4.5 – Performance comparison of the sequential and integrated approaches - 4^{th} part

The relative gap between the APV of these two approaches is reported in column 4. Small gap values confirm that the sequential approach is a good alternative to the integrated approach. Obviously, the solutions obtained with the integrated approach may have a lower OGV, which is offset by the value contributed by the financial decisions.

The second indicator (column 5) is the fill rate, which describes the ability to serve customers. Recall that the model is profit-oriented and that unsatisfied demands are lost. The fill rates of the integrated approach are mostly higher than those of the sequential approach. There are only 4 instances (with significant optimality gaps) whose fill rate is worst with the integrated approach. The higher fill rate with the integrated approach suggests that this approach favors larger investments that are made possible through the efficient use of financial decisions. Since OGV does not benefit from the leverage effect of the tax shield benefit, the sequential approach appears to be more conservative.

As the third, fourth, and fifth indicators are closely correlated, we briefly describe each of them, then we interpret the behavior of the integrated and sequential approaches according to them.

The third indicator is the Return On Equity (ROE) which represents the company's profitability from shareholders' point of view. It is computed as the ratio of the firm's net income ($NOPAT$) and the shareholders' equity ($Equity$). Hence, it expresses the net profit made by each unit of the shareholders' equity.

The fourth indicator, Return On Assets (ROA), measures the company's global profitability (paid income to both shareholders and debt-holders). It equals the net operating profit after taxes plus the after-tax interest ($NOPAT + interest \times (1 - \eta)$) divided by total assets (i.e., investment made by both shareholders and debt-holders). This indicator does not consider the impact of leverage on profitability.
Finally, the fifth indicator is the leverage ratio, which calculates the ratio of the firm's debt and total assets ($Debt/total\ assets$). Following the Modigliani and Miller reasoning, in our context, ROA and leverage should positively affect ROE.

In column 7, we report the average value of the ROA over the facility economic life. The ROA of the sequential approach is always higher than or equal to that of the integrated approach for two reasons. On the one hand, the additional investments with the integrated approach, in terms of profitability, are not as efficient as those chosen by the sequential approach. On the other hand, these additional investments increase the level of total assets (increasing the ratio's denominator).

Column 8 shows the average leverage ratio over the economic life of the facilities. This

ratio is not systematically higher or lower for the integrated approach. Probably since, in some cases, the integrated approach leads not only to more debt but also to higher assets level.

Similarly to ROA and leverage ratio, ROE, reported in column 6, is calculated as the average value over the economic life of facilities. This indicator is significantly related to the two indicators mentioned earlier. For most instances (49 out of 60), larger or equal ROE is obtained with the sequential approach. For 11 instance, ROE is higher with the integrated approach. In all of these cases, the leverage ratio of the integrated approach is higher than that of the sequential approach. The higher leverage ratio offsets the negative effect of lower ROA on ROE. For example, in the instance 60-C-G, ROA of the integrated approach is 9.27% (compared to 10.17%), but as the leverage ratio is 30.19% (compared to 28.65%), the integrated approach ends with a higher ROE (20.17% compared to 19.91%).

4.3.3 Detailed solutions resulting from the integrated and the sequential approaches

To better highlight the differences obtained by both approaches, Table 4.6 presents the detailed list of candidate facilities selected at each period (columns $t = 1$ to $t = 5$). The last column reports the total amount of investment in each solution (sum of the fixed cost of the selected facilities).

For most instances, the table shows slight differences between the networks found by both approaches. This table confirms that the integrated approach tends to favor larger investments than the sequential approach, or, when exactly the same facilities are selected, to invest earlier.

Table 4.6 shows the difference between the instances with random and growing demand. In the growing profile, the total demand increases between 5% to 25% at each time period. Hence, it yields a solution in which the facilities are selected gradually over the planning horizon. While in the random profile, the demand is more stable over the periods. Thus, it tends to open most of the required facilities earlier in the planning horizon. Opening all or most of the facilities early results in lower possible combinations than opening in different periods. This explains why the instances with growing demand are more challenging for the solver.

Instance	Approach	Facilities selected at each period					Investment
		t=1	*t=2*	*t=3*	*t=4*	*t=5*	(*rmu*)
60-R-R	Integrated	2 4					115 400
	Sequential	2 3					104 700
60-R-G	Integrated	3 5			4		154 700
	Sequential	3	5		4		154 700
60-C-R	Integrated	2 4					111 900
	Sequential	2			4		111 900
60-C-G	Integrated	2	6		4		153 300
	Sequential	2			4		111 900
90-R-R	Integrated	2 7 9			4		205 300
	Sequential	2 7	9				157 000
90-R-G	Integrated	2	9	4	7		205 300
	Sequential	2	9	4	7		205 300
90-C-R	Integrated	5 6			4		154 800
	Sequential	5 6			4		154 800
90-C-G	Integrated	2	7	9	4		206 000
	Sequential	2	7		6		162 600
120-R-R	Integrated	9 10 12	6		4		250 600
	Sequential	9 10 12		6	4		250 600
120-R-G	Integrated	9 12	10	6	4		250 600
	Sequential	9 12	10	6	4		250 600
120-C-R	Integrated	4 9 12			6		201 400
	Sequential	4 12			2 6		191 800
120-C-G	Integrated	4 12	9	2	6		243 700
	Sequential	12	4	9	6		201 400
150-R-R	Integrated	6 7 9 12 13 14		3	15		341 200
	Sequential	6 7 9 13 14		12	3		296 600
150-R-G	Integrated	7 9 13 14	6	12	3 15		341 200
	Sequential	7 9 13 14	6	12	3		296 600
150-C-R	Integrated	2 6 7 12 13 15		11	8		370 500
	Sequential	2 6 7 13 15		12	8		331 200
150-C-G	Integrated	6 7 13 15	2	12	8		331 200
	Sequential	6 7 13 15	2	12	8		331 200
180-R-R	Integrated	3 4 8 12 16 17			2		346 900
	Sequential	3 4 8 12 16 17			2		346 900
180-R-G	Integrated	3 4 6 8 12	7	17	2		400 700
	Sequential	3 4 8 12	6	7	2 17		400 700
180-C-R	Integrated	2 4 7 8 12 17			11 13		385 400
	Sequential	2 4 7 8 12 17			11		346 600
180-C-G	Integrated	4 8 12 17	2	7	11 13		385 400
	Sequential	4 8 12 17	2	7	11 13		385 400

Table 4.6 – Comparison of the supply chains yielded with the sequential and the integrated approaches -1st part

Instance	Approach	Facilities selected at each period					Investment
		t=1	*t=2*	*t=3*	*t=4*	*t=5*	(*rmu*)
210-R-R	Integrated	1 2 5 12 15	4	10 13	7		444 800
	Sequential	1 2 5 12 15		4 13	8 10		463 100
210-R-G	Integrated	1 2 5 12 14	4	10	8 13 15		514 200
	Sequential	1 2 12 15	5	13	4 8 10		463 100
210-C-R	Integrated	1 5 10 14 15		2 7	8 11		466 000
	Sequential	1 5 10 14 15		2 18	8		421 700
210-C-G	Integrated	5 8 10 15	1	14	2 7 11 18		505 000
	Sequential	1 5 10 15	18	14	2 8 11		466 000
240-R-R	Integrated	2 6 8 10 11 15 16 19 22 24			17		559 100
	Sequential	2 6 8 10 11 15 16 19 22 24			17		559 100
240-R-G	Integrated	2 6 10 11 16 19 24	15	8	22		505 800
	Sequential	2 6 10 11 16 19 24	15	8	22		505 800
240-C-R	Integrated	2 4 6 8 15 17 20 22 23 24			10		553 900
	Sequential	2 4 6 8 15 17 20 22 23 24			10		553 900
240-C-G	Integrated	2 6 8 15 17 20 22	4	24	10		507 700
	Sequential	2 8 10 17 20 22 23	4	15	6		503 200
270-R-R	Integrated	6 19 20 21 22 24 26			16 25		446 700
	Sequential	13 19 20 21 22 24 26			16		402 100
270-R-G	Integrated	8 19 20 21 22 26	6	25	16 24		498 400
	Sequential	8 19 20 21 22	25	26	16 24		453 800
270-C-R	Integrated	1 8 16 20 21 23 24 26			3 7 11		535 900
	Sequential	1 8 16 20 21 23 24			3 7 19		497 600
270-C-G	Integrated	8 16 20 21 23 24 26	11	1	3 7 19		592 200
	Sequential	8 20 21 23 24 26	16	1	3 7 11 19		592 200
300-R-R	Integrated	1 4 11 12 15 16 17 24 26		27			532 800
	Sequential	1 4 11 12 15 16 17 24 26		27			532 800
300-R-G	Integrated	1 4 11 14 15 16 26	17	12	24 27		579 300
	Sequential	1 4 15 16 24 26 27	17	12	11 14		579 300
300-C-R	Integrated	1 4 7 12 16 17 22 24 28	29		15		562 300
	Sequential	1 4 7 12 16 17 22 24 28			15		521 300
300-C-G	Integrated	1 4 7 12 22 24 28	16	17	11 15		576 000
	Sequential	1 4 7 12 22 24 28	16	17	11 15		576 000
330-R-R	Integrated	2 3 6 8 11 12 13 17 33		21	4		560 800
	Sequential	2 3 6 8 11 12 17 33			4 21		517 700
330-R-G	Integrated	2 3 4 6 11 12 33	3 13	17	8 21		560 800
	Sequential	2 3 4 6 12 33	11	17	8 21		517 700
330-C-R	Integrated	2 3 4 6 8 12 17 28 33			21 30		568 000
	Sequential	3 4 6 8 12 17 28 33			21 30		518 200
330-C-G	Integrated	3 8 12 17 28 33	2	4 6	21 30		568 000
	Sequential	3 4 8 17 33	12 28	6	2 21 30		568 000

Table 4.6 – Comparison of the supply chains yielded with the sequential and the integrated approaches - 2^{nd} part

Instance	Approach	Facilities selected at each period					Investment
		t=1	*t=2*	*t=3*	*t=4*	*t=5*	(*rmu*)
360-R-R	Integrated	4 7 8 15 17 22 23 26 27 28 30 34		1			649 700
	Sequential	1 4 7 8 15 17 22 23 26 27 30 34		28			649 700
360-R-G	Integrated	7 11 17 22 23 26 30 34	8 15	27 31	4 18		743 900
	Sequential	4 7 22 23 26 28 30 34	1 15	8 31	18 27	17	743 900
360-C-R	Integrated	4 7 15 17 23 25 26 28 30 32 33 34		22			663 700
	Sequential	4 7 15 17 23 25 26 28 30 32 33 34		22			663 700
360-C-G	Integrated	4 7 15 17 26 30 32 34	18 28	23 33	22 25		756 300
	Sequential	4 7 15 18 26 28 30 32 34	11 33	17	22 25	23	756 300
390-R-R	Integrated	4 6 11 17 19 20 22 24 27 28 31 33	23		5		715 800
	Sequential	4 6 11 17 19 20 22 24 27 28 31 33			5 23		715 800
390-R-G	Integrated	1 4 17 19 22 24 33	28	6 11 20 31	26 27		779 700
	Sequential	4 6 11 17 20 22 24 28 31	19	1 27	5 26 33		779 700
390-C-R	Integrated	1 4 5 6 14 17 19 22 28 32 33 35	27				699 200
	Sequential	1 4 5 6 14 17 19 28 31 32 33 35			22		687 800
390-C-G	Integrated	1 5 6 14 17 28 33 35	4 32	19	22 27 31		744 700
	Sequential	1 4 5 17 27 32 33 35	6 19	14	22 28 31		744 700
420-R-R	Integrated	12 14 15 21 22 28 31 41	3	13 24	7 35		661 600
	Sequential	3 12 14 15 21 22 28 35		41	7 31		554 200
420-R-G	Integrated	12 14 21 22 28 31 36	33 34	15 24	3 7 13 41		738 600
	Sequential	3 12 15 21 28	14	22 31	7 13 35 41		609 900
420-C-R	Integrated	3 12 21 39 40	22	8	5 36 41		507 800
	Sequential	3 12 21 39 40			5		318 200
420-C-G	Integrated	3 8 12 21 22	41	15	5 10 36 39 40		608 200
	Sequential	3 22 40	12	21	5 39		362 900
450-R-R	Integrated	12 15 22 24 25 26 29 35 36 45	23		5 19 31 38 44		771 600
	Sequential	12 15 22 24 25 26 29 34 35 36 45			5 19 31 44		733 100
450-R-G	Integrated	5 15 16 19 24 26 29 31 35 36 44	25 45	12 42	2 34 37		865 400
	Sequential	5 15 24 25 26 29 35 45	12 36	19	16 31 34 40 44	22	819 000
450-C-R	Integrated	8 12 19 26 34 36 45	5 15	14	2 23 24 29		703 400
	Sequential	5 12 14 19 26 29 36 45			1 15 23 34 43		646 000
450-C-G	Integrated	5 12 15 29 36 45	16 19 26	14	8 22 23 34		746 300
	Sequential	12 15 19 26 29 45	5	24	1 2 14 23 34 36		703 400
480-R-R	Integrated	5 11 18 19 20 21 23 28 31 32 35 36 37	48	41	17 34		900 300
	Sequential	5 11 17 18 19 20 21 23 28 31 32 35 36 37 48		7	41		900 300
480-R-G	Integrated	5 11 20 21 23 28 31 32 35 36 41	18 19	7 22	12 17 37 48		988 600
	Sequential	5 11 18 19 20 21 28 31 32 35 36	17 23	7 48	41 43	37	954 700
480-C-R	Integrated	5 11 17 21 23 24 28 37 39 41 46	22 36 43	31 18 48			932 700
	Sequential	5 11 17 21 23 28 31 35 36 37 41 43 46 47 48		22	18		887 600
480-C-G	Integrated	5 17 21 23 28 35 41 42 43 47 48	11 31 46	4 22	36 37 38 39		1 010 500
	Sequential	5 17 21 23 28 31 36 41 43 46 48	35 39	37 38	18 22 26	11	981 800

Table 4.6 – Comparison of the supply chains yielded with the sequential and the integrated approaches - 3^{rd} part

4.3.4 Detailed results of instance 120-C-G

To get a detailed picture of the decision-making mechanism, we illustrate the solutions found by the integrated and sequential approaches on instance 120-C-G. This instance has four markets (A, B, C and D) and 12 candidate facilities, whose features are detailed in Tables 4.7 and 4.8, respectively.

Market	Economic index	Opening cost parameter (φ) (rmu)	Selling price (p) ($rmu/unit$)
A	88	670	3.62
B	57	630	3.22
C	140	740	4.67
D	124	725	4.48

Table 4.7 – Instance 120-C-G: market parameters

Facility	Market	Capacity ($capa$) ($units/period$)	Opening cost (o) (rmu)	Fixed yearly running cost (f) ($rmu/year$)	Processing cost (μ) ($rmu/unit$)
1	A	3 500	39 600	1 980	1.03
2	B	4 500	42 300	2 115	1.31
3	C	3 500	37 300	1 865	1.03
4	B	6 000	48 800	2 440	1.29
5	B	4 500	42 300	2 115	1.00
6	A	6 000	51 900	2 595	0.99
7	D	3 500	42 900	2 145	1.15
8	A	4 500	44 900	2 245	1.00
9	A	6 000	51 900	2 595	1.10
10	D	4 500	44 900	2 245	1.12
11	C	3 500	42 900	2 145	1.34
12	A	6 000	48 800	2 440	0.99

Table 4.8 – Instance 120-C-G: facility parameters

Figures 4.2 and 4.3 present maps with the optimal network configurations obtained under the integrated and sequential approaches, respectively. These maps show the 4 markets A, B, C, and D with their borders (solid red lines). The facilities selected at each period appear in different shades of green. Non selected facilities appear in gray color.

The served customers are represented by blue circles while the customers with unsatisfied demands are represented in gray color.

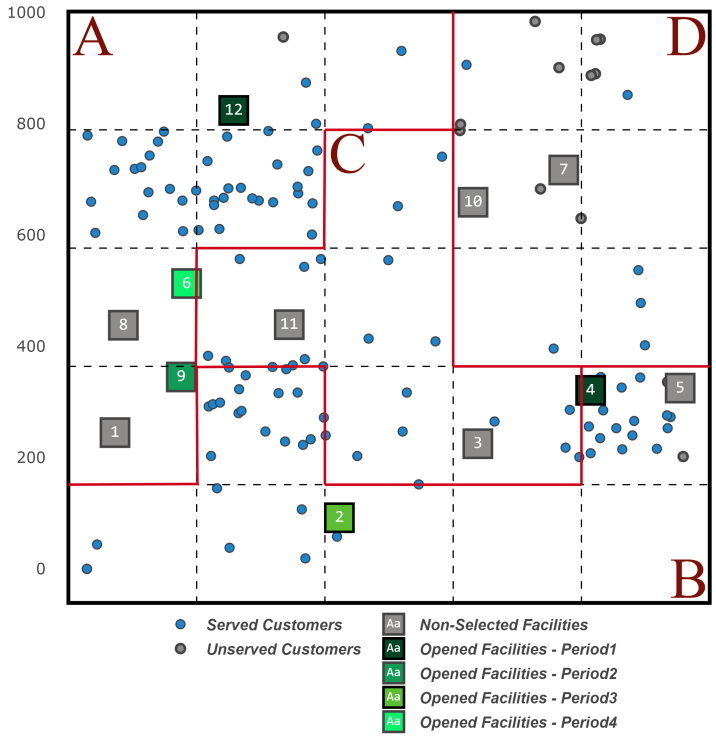

Figure 4.2 – Instance 120-C-G – Solution obtained with the integrated approach

As presented in Table 4.6, the integrated approach opens facility 12 and 4 at period 1, facility 9 at period 2, facility 2 at period 3, and facility 6 at period 4. The sequential approach opens facility 12 at period 1, facility 4 at period 2, facility 9 at period 3, and facility 6 at period 4.

Table 4.9 details the value of equity, debt, tax shield benefit, expected bankruptcy cost and probability of bankruptcy for both solutions (columns 2 to 6). It also compares the value of OGV and APV (columns 7 and 8)

Solution Approach	Equity	Loan Balance	Tax Shield Benefit	EBC	Proba. of bankruptcy	Objective function OGV	APV
Integrated	139 505	114 116	7 692	980	4.1%	47 838	**54 550**
Sequential	123 052	93 590	6 044	835	3.5%	**47 959**	53 168

Table 4.9 – Value of the financial indicators in the integrated and sequential based solutions

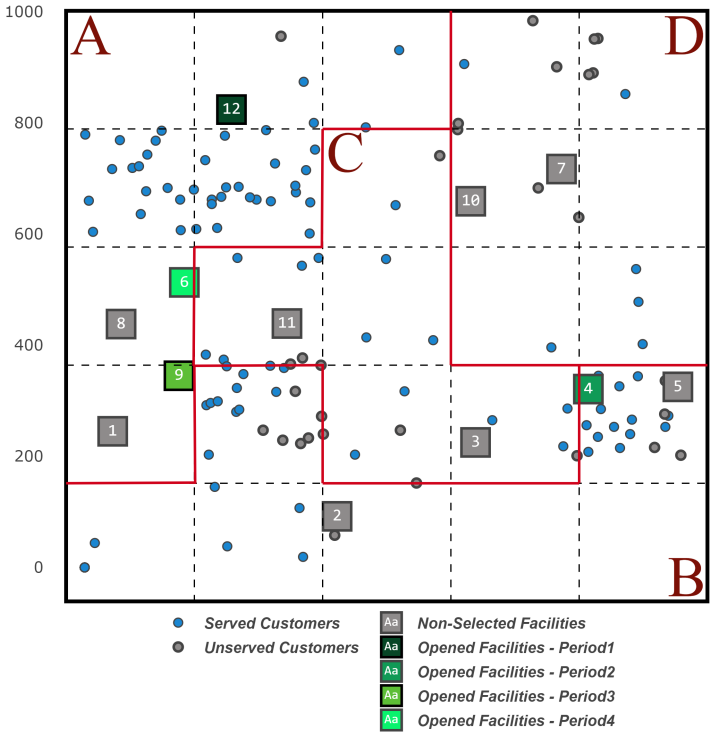

Figure 4.3 – Instance 120-C-G – Solution obtained with the sequential approach

The first difference between both solutions is the opening time of facility 4. Opening this facility at period 1 in the integrated approach slightly reduces the value of OGV but increases the value of total assets at period 1; this increases the debt ratio's denominator and gives more opportunity to borrow ($borrow_1 = 76\,544$ rmu with the integrated approach, versus $borrow_1 = 38\,625$ rmu with the sequential approach). An immediate consequence is the increase of the tax shield benefit. Besides, as the value of the debt ratio at the first period is 0.7 in both approaches, the additional investment by the integrated approach does not increase the probability of bankruptcy. A similar mechanism explains why facility 9 is opened earlier with the integrated approach. The last difference between both solutions concerns facility 2. The firm's total assets at the end of the second period are higher with the integrated approach. It allows the firm to use debt financing for opening facility 2 which results in a higher tax shield benefit. But, this investment slightly decreases the OGV. Moreover, it increases the firm's liabilities leading to a higher probability of bankruptcy. Nevertheless, the higher bankruptcy cost is offset by the higher tax shield benefit, which eventually yields a slightly higher firm value with the integrated approach.

Another consequence concerns the market coverage. A higher fill rate is achieved with the integrated approach ($fill\ rate = 83\%$, versus 64%), due to larger and earlier investments.

The results for ROA, ROE, and leverage ratio (shown in Table 4.5) are also consistent. As expected, ROA of the integrated approach is lower than that of the sequential approach (8.27% versus 9.18%). Although the average income paid to both shareholders and debt-holders ($NOPAT + interest \times (1 - \eta)$) is higher on average with the integrated approach (14 404 rmu versus 13 635 rmu), the value of total assets is also higher on average (174 143 rmu versus 148 533 rmu).

Besides, the leverage ratio of the integrated approach is also lower than the sequential approach (30.77% versus 31.28%). These two factors positively affect the ROE. As both are lower with the integrated approach, a lower ROE with the integrated approach is expected (17.59% versus 20.71%). Correspondingly, the lower leverage explains why the gap between ROE is higher than the gap between ROA. The integrated approach generates more money for the investors but at a lower rate of return.

4.4 Conclusion

This chapter explained the procedure of generating test instances with different sizes in order to evaluate the proposed mathematical model. In generating the data, we defined two different configuration patterns concerning the location of candidate facilities and customers. We also generated the customers' demand based on two random and growing patterns. Moreover, to better illustrate the impact of financial decisions on the SCND process, we generated different markets standing for different financial situations.

In particular, and in order to highlight the impacts of integrating financial decisions into the SCND process, we proposed two approaches to solve the mathematical model: the integrated approach, which simultaneously optimizes operational and financial decisions, and the sequential approach, which first sets the operational decisions and then arranges the financial decisions for the network designed in the previous step.

Regarding the difficulty of estimating the probability of bankruptcy, we assessed two methods: i) the Altman Z-score method, and ii) the debt ratio method. Among them, we came up with choosing the latter to be implemented.

The computational experiments in Section 4.3 show that, for both approaches, instances of realistic size can be solved to optimality by a MILP solver, the sequential

approach being slightly easier to solve.

The computational experiments also show that considering financial features into facility location models slightly modifies both the spatial layout of the logistics network and its implementation on a strategic time horizon. Thus, maximizing the APV helps taking supply chain strategic decisions that are consistent both from a logistic and a financial point of view.

As far as solution methods are concerned, the costly linearization mechanism prevents MILP to solve larger instances. We identified the limitations imposed by calculation time and memory size in determining the exact solution of the proposed mathematical model. Our experiments suggest that solving large-sized instances would require either to use heuristic methods or to hybridize exact and heuristic methods.

Chapter 5

A Large Neighborhood Search Approach

The numerical experiments in Chapter 4 reveal that the model presented in Chapter 3 is tractable for the reasonable-size instances by the state-of-the-art solvers. However, they also indicate the limitations imposed by calculation time in determining the exact solution of the proposed mathematical model. Thus, developing a meta-heuristic/heuristic method is suitable for finding good solutions, in a reasonable time, particularly for large-sized instances. The Large Neighborhood Search (LNS) is one of these algorithms that has proven its efficiency and adaptability in addressing various optimization problems, including logistic and SCND problems. Therefore, this chapter aims to develop an LNS-based solution method to find optimal/near-optimal solutions for instances presented in Chapter 4.

This chapter is organized as follows. Section 5.1 introduces the LNS metaheuristic. Section 5.2 explains how the LNS algorithm can be adapted to our SCND model. Sections 5.3, 5.4, and 5.5 describe different algorithms developed to determine the main decision variables as well as the set of LNS removal and repair operators. Section 5.6 reports the numerical results of LNS implementation. Finally, section 5.7 concludes the chapter.

5.1 Introduction on LNS for SCND

In 1998, Shaw [1998] proposed a heuristic called *Large Neighborhood Search (LNS)* for a constraint programming framework. LNS helps navigate in a large and complex solution space easily using problem-dependent heuristics. The large neighborhood search allows to find better candidate solutions and track a more promising path.

The underlying principle of the LNS is improving an incumbent solution by iteratively removing and repairing a part of it. This procedure uses several problem-dependent *destroy* and *rebuild* operators. First, a destroy operator is applied to destruct a part of the

solution; then a repair operator is invoked to rebuild the destroyed solution. Using a destroy operator immediately followed by a rebuild operator thus yields a neighbor solution. The selection of these operators typically includes stochastic rules, allowing to explore different neighborhoods.

Algorithm 1 shows the general steps of the LNS in a maximization context.

Algorithm 1: Main scheme of the Large neighborhood Search (LNS)

```
1  Initial solution: S^0
2  Best solution: S* ← S^0
3  Current solution: S ← S^0
4  while the termination criterion is not satisfied do
5  |  Selection of removal and repair operators
6  |  S' ← Repair(Removal(S))
7  |  Denote Z' and Z* as the objective of S' and S*, respectively
8  |  if Z' > Z* then
9  |  |  S* ← S'
10 |  |  S ← S'
11 |  |  else if S' is accepted according to the acceptance criterion then
12 |  |  |  S ← S'
13 |  |  end
14 |  end
15 end
16 Return S*;
```

It starts with an initial solution (line 1) which is gradually improved by iterative use of destroy and repair operators (lines 5 and 6). If the incumbent solution dominates the preceding best solution, it is saved as the new best solution (lines 7-10). The acceptance criterion (line 11) defines conditions under which the new solution will be accepted as the new incumbent. Its main idea is to accept solutions with slight degradation of the objective function in order to escape from local optima. Thus, the new solution may be accepted even though it deteriorates the objective function (lines 11-13).

The adaptability and flexibility of LNS in defining operators make this technique suitable for different applications. Hundreds of scientific publications report the use of LNS for solving the Vehicle Routing Problem (VRP) and its extensions (see, e.g., [Korsvik et al., 2011, Demir et al., 2012, Hemmelmayr et al., 2012, Hiermann et al., 2016, Quirion-Blais et al., 2017, Sacramento et al., 2019, Dumez et al., 2021, Tellez et al., 2022]), public transport [Schmid, 2014, Wen et al., 2016, Canca et al., 2017], lot-sizing [Muller et al., 2012],

scheduling [Lin and Ying, 2014, Sacramento et al., 2019]. In addition, LNS has been used for SCND and facility location problems. Pereira et al. [2015] propose a hybrid LNS-based heuristic approach to solve a probabilistic maximal covering location-allocation problem. LNS is employed to determine the location solutions, while the allocations are optimally solved using the exact approach in each iteration. This method solves 94.5% of instances to optimality. de Sá et al. [2015] develop and compare several solution approaches for a hub-location problem. A Benders decomposition algorithm is used to solve small instances to optimality. For larger instances, the authors proposed a Variable Neighborhood Descent (VND), a Greedy Randomized Adaptive Search procedure (GRASP), and a Large Neighborhood Search(LNS). The computational experiments show that both the GRASP and the LNS are able to find high-quality solutions in a reasonable time.

Eskandarpour et al. [2017] use an LNS solution method to solve a four-echelon single-period multi-product SCND problem. Similarly to Pereira et al. [2015] the LNS algorithm is used to decide about the location of facilities, while transportation modes and product flow decisions are determined by a greedy heuristic. To evaluate the developed solution method, a set of generated instances with different sizes is solved using IBM Cplex and the proposed LNS algorithm. This comparison reveals the stability and efficiency of LNS.

Souto et al. [2021] present a hybrid solution approach to solve a two-stage capacitated facility location problem aiming at minimizing the operating costs. They hybridize an LNS with a Clustering Search and Local-Branching. The proposed method compares favorably with respect to other relevant approaches in the literature, both in terms of the solutions' quality and of CPU time.

In addition, some recent references use the LNS method for location-routing problems, such as Schiffer and Walther [2018], Mohri et al. [2018], Real et al. [2021], Bayraktar et al. [2021].

5.2 LNS framework for our SCND model

This section explains how the general framework of LNS is adapted to our mathematical model. In particular, it deals with three main decision variables which values fully determine the solutions: i) facility location (binary variables), ii) product flows within the network (continuous variables), and iii) choice of financial variables (continuous variables).

The impact of binary location variables is more global than that of continuous variables, corresponding to more local decisions. Figure 5.1 illustrates the process to determine

the value of all decision variables in each LNS iteration. The key decision is to determine the operating facilities' set and their opening periods (see section 5.3). Afterward, the product flows are determined (see section 5.4) and then the financial variables (see Section 5.5).

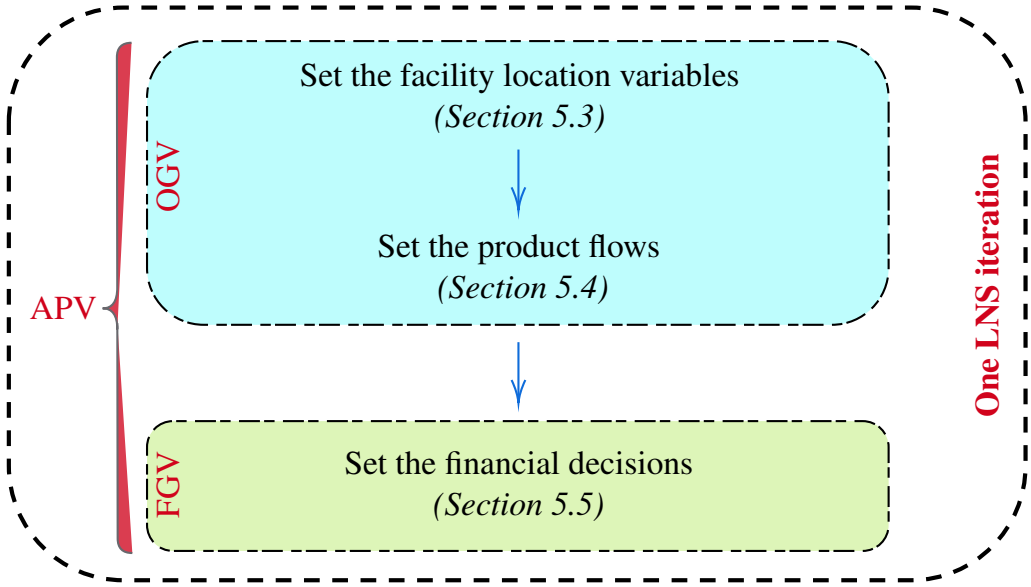

Figure 5.1 – Sequence of decisions in one LNS iteration

Algorithm 2 gives a more detailed view of the way a SCND model is solved with an LNS approach.

Initial Solution: The initial solution is determined using the Cplex solver. To find this solution, we maximize OGV in the logistic sub-problem (1^{st} sub-problem presented in the sequential approach). The LNS is initialized with the first feasible solution found by Cplex.

Facility Location Variables: Each LNS iteration modifies the facility location variables. This change consists either in shifting the opening time of a facility or replacing a facility. All changes are done according to a set of removal and repair operators, which are explained in Section 5.3.

Product Flows and Financial Decisions: Once the facilities are established, the product flows are determined with a procedure explained in Section 5.4, and financial decisions are set according to a procedure explain in Section 5.5. This yields a completely

Algorithm 2: Framework of LNS for our SCND model

Initial solution: S^0
Best solution: $S^* \leftarrow S^0$
Current solution: $S \leftarrow S^0$
Σ^-, Σ^+ `// Set of removal and repair operators`
$counter \leftarrow 0$
for $iter = 1$ *to* $iterMax$ **do**
  if *counter=500* **then**
    $S \leftarrow \text{swap}(S)$
    $counter \leftarrow 0$
  end
  else
    $counter \leftarrow counter + 1$
    Randomly choose between *"replace"* and *"shift"*
    if *"replace"* **then**
      $\sigma^- \leftarrow select(\Sigma^-)$ `// Randomly select a removal operator`
      $\sigma^+ \leftarrow select(\Sigma^+)$ `// Randomly select a repair operator`
      $S' \leftarrow \sigma^+(\sigma^-(\text{S}))$
    end
    else if *"shift"* **then**
      $\sigma \leftarrow select(\Sigma^-)$ `// Randomly select a shift operator from` Σ^-
      $direction \leftarrow$Randomly choose between *"forward"* and *"backward"*
      $S' \leftarrow \sigma(S, direction)$
    end
  end
  $S' \leftarrow$ set the product flows (see section 5.4)
  $S' \leftarrow$ set the financial decisions (see section 5.5)
  Denote $Z_{S'}$ and Z_{S^*} as the objective function of solution S' and S^*
  if $Z_{S'} > Z_{S^*}$ **then**
    $S^* \leftarrow S'$
    $S \leftarrow S'$
  end
  else
    if *Acceptance Criterion(S')* **then**
      $S \leftarrow S'$
    end
  end
end
Return S^*

repaired and feasible solution S'. Note that the sequence of decisions in one LNS iteration is similar to the sequential approach presented in Chapter 4.

Acceptance Criterion: In line 33 of Algorithm 2, the acceptance criterion evaluates the incumbent solution to decide whether if should be accepted as the current solution at the next iteration. There are several possible acceptance criteria in LNS [Santini et al., 2018]. Among them, we use the record-to-record criterion proposed by Dueck [1993]. Record-to-record states that a solution is accepted if the gap between its objective value and the best known objective value is smaller than a certain threshold. Dueck [1993] also proposes to use a large value as the initial threshold, which drops to 0 (or a predetermined value) gradually in each iteration of LNS. To avoid parameter tuning and get a reliable acceptance criterion Dumez et al. [2021] propose a simple adaptive procedure to set the record-to-record threshold: the rate of accepted solutions is evaluated periodically. Then, whenever required, the acceptance threshold is modified to keep the rate of accepted solutions in a specific range.

Stopping Criterion: The stopping criterion is based on a maximum number of iterations denoted by $IterMax$. However, other classical criteria such as the number of iterations without improvement and computing time limit would be possible.

5.3 Determining the set of open facilities and their opening time

We define three types of operators to determine the facilities' set and opening time: *replace*, *shift*, and *swap*. The choice between *replace* and *shift* is made randomly in each LNS iteration, while the *swap* is called periodically. *Replace* results in a change to the facilities' set; *shift* ends up with a change in the facilities' opening time; and, *swap* exchanges two selected facilities.

5.3.1 Replace

The *replace* procedure (lines 14–18 of Algorithm 2) uses a set of removal and repair operators to replace a facility. The choice between these operators is made randomly.

5.3.1.1 Removal operators

The aim of the removal operators is to de-select a facility from the current solution.

1. **Random removal**: this operator randomly chooses one facility to be removed from the solution. It aims at diversifying the search in the solution space.

2. **Unit cost removal**: this operator removes a facility with the least performance in terms of fixed cost and capacity utilization. For each facility, we measure the ratio of the average unused capacity during its lifetime over its fixed cost. The operator ranks the facilities according to this ratio and removes one based on a biased roulette wheel.

3. **OGV-based removal**: this operator removes one of the facilities with the least value contributed in OGV. According to the constraints (3.12), OGV can be broken down into the value contributed by each facility, that we define as a score OGV_j, for all $j \in \mathcal{J}$. All operating facilities are ranked in non-increasing order of their score OGV_j. Finally, one facility with a low score is selected for removal according to a biased roulette wheel selection.

5.3.1.2 Repair operators

Applying the removal operators leads to a partially destroyed solution. The goal of repair operators is to rebuild a feasible solution by re-inserting new facilities into the partial solution. We have implemented three repair operators. In each LNS iteration, the choice between these operators is done randomly. Note that the opening time of the selected facility is set at the same value as the recently destroyed facility.

1. **Random repair**: Among the set of non-selected facilities, this operator randomly chooses one facility to be added to the solution. Likewise the removal phase, this operator aims at diversifying the search in the solution space.

2. **Unit cost repair**: this operator favors facilities with a higher capacity and lower fixed costs. For each candidate facility, the ratio of opening cost and capacity is calculated. Since smaller values of this ratio are more desirable, one facility with a low ratio will be selected according to the roulette wheel principle.

3. **OGV-based repair**: the idea of this operator is to add one of the most promising facilities to the partially destroyed solution. Assuming that the assignment of customers to the operating facilities (in the destroyed solution) remains the same, an OGV estimation is made for the candidate facilities, called OGV_j. First, the unassigned customers are assigned to the candidate facilities (one by one) according to a greedy heuristic (see Section 5.4.3). Then, the candidate facilities are ranked according to the estimated OGV_j, and one is added to the solution applying the roulette wheel principle.

5.3.2 Shift

In the *shift* procedure (lines 19–23 of Algorithm 2), a facility is first selected according to one of the removal operators (i.e., random, unit cost, OGV-based). Then, a shifting direction (forward or backward) is chosen randomly. Finally, the opening time of the selected facility is shifted by 1 period in the chosen direction. If the opening time of the selected facility is 1 (resp. T), it is shifted forward (resp. backward).

5.3.3 Swap

The *swap* operator (line 8 of Algorithm 2) modifies the opening time of facilities, i.e. the set of time periods during which facilities are open. This impacts both OGV and APV. The *swap* operator exchanges the opening time of two operating facilities: it examines all the possible opening time swaps of two operating facilities and chooses the most efficient one. This operator helps accelerate the convergence of the LNS algorithm but it is time-consuming due to the number of time swaps evaluated. Thus, it is called periodically, every 500 iterations.

5.4 Product flows

Each LNS iteration involves deciding the product flows, once variables y_{jt} have been determined. At each period, customers' demands must be assigned to one or several open facilities (the model does not include any single sourcing constraint) and the quantities traveling between the facilities and the customers must be determined.

This optimization problem corresponds to a generalization of the well-known assignment problem, with multiple periods. We first give a mathematical formulation and then

we propose two approaches to solve it: *i*) by using a solver and *ii*) by developing a heuristic approach.

5.4.1 Mathematical formulation of the assignment problem

Assignment is a well-known problem in the operations research literature. The Generalized Assignment Problem (GAP) is a classical combinatorial optimization problem in which a set of I tasks must be optimally assigned to a set J of machines. Assigning task $i \in I$ to machine $j \in J$ generates a profit s_{ij} while it consumes the quantity q_{ij} of the machine capacity c_j. The objective function of GAP is to assign task $i \in I$ to machine $j \in J$ in a way that maximizes the total profit respecting the capacity of the machines. This problem can be expressed in the form of the following mathematical model.

$$Max \sum_{i \in I} \sum_{j \in J} s_{ij} x_{ij} \tag{5.1}$$

$$\sum_{i \in I} q_{ij} x_{ij} \leq c_j \qquad \forall j \in J \tag{5.2}$$

$$\sum_{j \in J} x_{ij} \leq 1 \qquad \forall i \in I \tag{5.3}$$

$$x_{ij} \in \{0, 1\}$$

Note that the binary variable x_{ij} takes value 1 if task $i \in I$ is assigned to machine $j \in J$. This problem is classified as NP-hard.

The GAP can be extended to find an assignment of customers' demands to facilities that maximize the value of OGV:

- **Sets and indices:** The set of tasks and the set of machines in the GAP represent the set of customers and the set of facilities, respectively. As we deal with a multi-period model, an index $t \in \mathcal{T} \cup \mathcal{T}'$ is defined.

- **Operating facilities:** We recall that set of open facilities is already determined, thus the value of variables y_{jt} can be replaced by their value 0 and 1. This avoids to assign customers to non-operating facilities.

- **Accessibility:** Due to trade rules between geographical areas as well as various logistic constraints, some customers might not be delivered by some facilities. We

recall that the parameter V_{ij} takes value 1 if customer $i \in I$ can be delivered from facility $j \in J$, and 0 otherwise.

- **Discounting rate:** To consider the impact of the time value of money, the profit earned in each period is discounted by the cost of equity r_E.
- **Profit elements:** the profit is a function of three parameters; (i) P_i: unit selling price to customer i, (ii) μ_j: unit manufacturing cost of facility j, and (iii) $w \times dist_{ij}$ transportation cost between facility j and customer i.
- **Variables:** We define the following variables:
  - q_{ijt} expresses the quantity shipped from facility $j \in J$ to customer $i \in I$ at period $t \in \mathcal{T}$.
  - x_{it} equals 1 if customer i is served at period t, and 0 otherwise.
  - s_{ijt} is the amount of profit earned at period t by shipping q_{ijt} unit from facility j to customer i.
- **Objective function:** The objective is to maximize the discounted profits earned in all periods $\mathcal{T} \cup \mathcal{T}'$.

Now we describe the mathematical model of our assignment problem by extending the mathematical model (5.1)–(5.3).

$$Max \sum_{i\in I}\sum_{j\in J}\left[\sum_{t\in\mathcal{T}}\frac{y_{jt}\ s_{ijt}}{(1+r_E)^t}+\sum_{t\in\mathcal{T}'}\frac{y_{jt}\ s_{ijT}}{(1+r_E)^t}\right] \tag{5.4}$$
$$=\sum_{i\in I}\sum_{j\in J}\left[\sum_{t\in\mathcal{T}}\frac{y_{jt}\left[(P_i-\mu_j-w\ dist_{ij})\ q_{ijt}\right]}{(1+r_E)^t}+\sum_{t\in\mathcal{T}'}\frac{y_{jt}\left[(P_i-\mu_j-w\ dist_{ij})\ q_{ijT}\right]}{(1+r_E)^t}\right]$$

$$\sum_{i\in I} q_{ijt} \le c_j \qquad \forall j \in J, t \in \mathcal{T} \tag{5.5}$$

$$q_{ijt} \le v_{ij}\ d_{it}\ y_{jt} \qquad \forall i \in I,\ j \in J,\ t \in \mathcal{T} \tag{5.6}$$

$$\sum_{j\in J} q_{ijt} = d_{it}\ x_{it} \qquad \forall i \in I,\ t \in \mathcal{T} \tag{5.7}$$

$$x_{i,t-1} \le x_{it} \qquad \forall t \in \mathcal{T} \tag{5.8}$$

$$x_{it} \in \{0,1\}, q_{ijt} \ge 0$$

The above mathematical model aims at maximizing the sum of discounted profits over the whole planning horizon. The first part of the objective function measures the discounted profit earned over the logistics horizon $\mathcal{T}$. The second part measures the discounted profit beyond the logistics horizon ($\mathcal{T}'$). It is added due to the assumption of the model presented in Chapter 3. We assume that the cash flows generated at period T are repeated for some (specific) periods beyond T (see Figure 3.2).

Constraints (5.5) is the multi-period version of constraint (5.2). Constraints (5.6) restricts the quantity shipped from facility j to customer i. Some customers are not accessible from some facilities (v_{ij}), the amount of quantity shipped cannot exceed the demand d_{it}, and a non-operating facility cannot deliver products (y_{jt}). Constraints (5.7) and (5.8) model two assumptions already mentioned in Chapter 3. The former forbids partial delivery: at period t, customer i should be either satisfied completely ($= d_{it}$) or not at all ($= 0$). The latter expresses that once a customer is served, it should be served in the following periods.

The above assignment problem can be solved either to optimality by using a solver, or an approximate solution can be found by ad hoc heuristics, as presented in the next subsections. Later, in section 5.6, we draw a comparison between the two approaches consisting in solving the assignment problem with Cplex or with the heuristic.

5.4.2 Solving the assignment problem using Cplex

Since this problem is solved in every LNS iteration, long CPU times are not affordable. LNS contains thousands of iterations; thus, spending much time solving the assignment problem costs a large part of the time budget. Therefore, we seek a relatively efficient approach to solve the assignment problem with acceptable quality. We propose four different approaches to solve the assignment problem using the Cplex solver. First, we maximize the OGV in the logistic sub-problem (3.1) – (3.15) (1^{st} sub-problem presented in the sequential approach) by fixing the facilities' set and opening time (already determined in the previous level of LNS). Second, we solve the assignment model (5.4)–(5.8) without any specific condition. The main difference is that the second approach contains only one main decision variable q_{ijt}, which value automatically determines all other variables. Third, we solve the assignment model (5.4)–(5.8) by setting the target optimality gap to 1%. Fourth, we propose a relaxed version of the assignment model (5.4)–(5.8). Variables x_{it} are assumed continuous in the interval $[0, 1]$ and the model is solved with Cplex with standard tuning.

These four approaches have been compared on a restricted benchmark set of 9 instances, representing different instance sizes, geographical patterns, and demand patterns. Each instance is solved 3 times. Table 5.1 reports the average and the best CPU times necessary to solve the assignment problem in each LNS iteration.

Instance	Logistic Sub-problem		Assignment Model		Assignment Model (MIP Gap =1%)		Assignment Model (Relaxed x_{it})	
	Average	Best	Average	Best	Average	Best	Average	Best
60 - R - R	4.52	3.37	0.23	0.20	0.06	0.04	0.01	0.01
60 - C - G	3.80	3.21	0.28	0.19	0.05	0.04	0.01	0.01
90 - R - G	72.94	70.30	7.07	5.85	0.20	0.15	0.04	0.03
90 - C - R	47.13	37.15	1.14	0.54	0.08	0.05	0.03	0.03
120 - R - R	82.33	70.50	13.20	11.58	0.36	0.27	0.11	0.09
120 - C - G	20.57	20.57	5.69	3.35	0.31	0.26	0.15	0.14
150 - R - G	29.94	22.33	7.02	6.94	0.28	0.24	0.14	0.12
150 - C - R	37.08	35.44	9.61	7.21	0.37	0.30	0.17	0.15
180 - R - R	112.28	105.42	24.24	20.25	0.47	0.39	0.28	0.25
180 - C - G	84.69	79.30	20.76	18.84	0.35	0.28	0.17	0.15
210 - R - G	99.63	99.63	21.85	17.97	0.38	0.31	0.22	0.18
210 - C - R	121.10	104.08	26.46	23.66	0.44	0.38	0.17	0.16
240 - R - R	131.21	118.85	20.48	18.89	0.39	0.36	0.18	0.15
240 - C - G	75.69	66.94	14.63	13.25	0.28	0.24	0.17	0.15
270 - R - G	159.91	127.56	31.11	27.56	0.55	0.48	0.28	0.22
270 - C - R	147.50	139.65	24.32	21.25	0.37	0.31	0.20	0.17
300 - R - R	110.58	103.98	35.86	31.64	0.86	0.77	0.30	0.26
300 - C - G	142.36	115.66	28.63	25.26	0.57	0.49	0.33	0.30

Table 5.1 – Comparison of four assignment approaches (CPU times in seconds)

Table 5.1 indicates that the relaxed assignment model takes the minimum CPU time. However, in addition to the CPU time, the quality of the solution must also be evaluated. Thus we report the optimality gaps of the last two approaches in Table 5.2. Note that the negative gaps with the fourth approach are due to the relaxation of x_{it}; thus, the solution obtained is an upper bound to the optimal solution.

Small gaps value reveal sufficiently close assignments obtained by both approaches—however, slightly better performance with the relaxed assignment approach can be noticed. The average gap between the optimal objective of the assignment problem and the objective obtained by the third approach is 0.21% while it is -0.07% for the fourth approach.

Instance	Assignment Model (MIP Gap = 1%)	Assignment Model (Relaxed x_{it})
60 - R - R	0.17	- 0.03
60 - C - G	0.29	- 0.11
90 - R - G	0.19	- 0.22
90 - C - R	0.43	- 0.14
120 - R - R	0.28	- 0.07
120 - C - G	0.15	- 0.02
150 - R - G	0.22	- 0.03
150 - C - R	0.09	- 0.01
180 - R - R	0.07	- 0.01
180 - C - G	0.18	- 0.02
210 - R - G	0.11	- 0.05
210 - C - R	0.09	- 0.04
240 - R - R	0.24	- 0.09
240 - C - G	0.21	- 0.02
270 - R - G	0.42	- 0.08
270 - C - R	0.25	- 0.12
300 - R - R	0.13	- 0.04
300 - C - G	0.32	- 0.11
Average	*0.21*	*- 0.07*

Table 5.2 – Comparison of two last assignment approaches (optimality gap in %)

According to these observations, the fourth approach is ahead of others regarding both the computational times and the quality of the solutions found.

5.4.3 Greedy heuristic for customer assignment

We propose a greedy heuristic approach based on the notion of marginal profit. Let us define the marginal profit, denoted by a_{ij}, as the profit earned by shipping one unit from facility $j \in J$ to customer $i \in I$. It is expressed as:

$$a_{ij} = P_i - \mu_j - w\ dist_{ij} \quad \forall\ i \in I,\ j \in J$$

We define a matrix of marginal profits denoted by $A = [a_{ij}] \quad \forall\ i \in I,\ j \in J$.

Algorithm 3 presents the main stages of the heuristic approach.

All customers $i \in \mathcal{I}$ are initially not assigned to any facility. Then, customers are

Algorithm 3: Customer assignment based on marginal profit

```
   Input: I                                                  // set of customers
   Input: A                                          // matrix of marginal profits
 1 for t = 𝒯 to t = 1 do
 2 |   I' ← I                                       // set of unassigned customers
 3 |   J* ← operating facilities at period t
 4 |   Cap_j ← total capacity of facility j
 5 |   while J* is not empty AND I' is not empty do
 6 |   |   (i, j) = argmax a_ij  ∀i ∈ I', j ∈ J*
 7 |   |   if d_it ≤ Cap_j then
 8 |   |   |   q_ijt = d_it
 9 |   |   |   Cap_j = Cap_j − d_it
10 |   |   |   I' ← I' \ {i}
11 |   |   else
12 |   |   |   J* ← J* \ {j}
13 |   |   end
14 |   end
15 |   I ← I − I'
16 end
17 Return q_ijt
```

assigned to facilities period after period, starting from period $\mathcal{T}$ backward to period 1. We recall that, from constraints (5.8), once a customer is served, it should be served in the following periods. Thus, the overall quantity of goods delivered to all customers is non-decreasing. Thus, the heuristic starts by assigning the demand at period $\mathcal{T}$, which is the most critical.

The operating facilities and unassigned customers are stored in sets J^* and I', respectively. In each period $t \in \mathcal{T}$, unassigned customers are assigned to the operating facilities one by one as long as there is remaining capacity or until there is no customer left to be assigned (line 5). Lines 6–13 are dedicated to the assignment of unassigned customers to the operating facilities. The algorithm finds the customer and facility pair (i, j) with the maximum marginal profit. If the remaining capacity of facility j is enough for the whole demand d_{it}, then customer i is assigned to facility j. Here, q_{ijt} takes value d_{it} and the capacity of facility j is updated accordingly. Then, customer i is removed from I'. If the demand exceeds the remaining capacity of facility j, then facility j is removed from the set J^*.

In line 15, the customers who are not served at the current period will not be further

considered in the next iterations. In the end, the algorithm returns the value of product flow variables q_{ijt}.

5.5 Financial decisions

Once OGV is determined, FGV can be calculated according to the amount of debt borrowed during the planning horizon. FGV is a function of tax shield benefit and expected bankruptcy cost.

$$FGV = (1 - \pi)\eta \sum_{t \in \mathcal{T}} \frac{I_t}{(1 + \alpha)^t} - \pi\ \gamma\ OGV. \tag{5.9}$$

Borrowing increases the tax shield benefit (first term in equation (5.9)), while on the other side, it increases the expected bankruptcy cost (second term in equation (5.9)) due to the increase in the probability of bankruptcy, π. Therefore, the maximum FGV can be achieved by finding the best trade-off between tax shield benefit and expected bankruptcy cost.

Algorithm 4 describes a two-step heuristic approach to maximize FGV. The first step (lines 1-7) sets the borrow to its maximum possible value. In other words, all investments are funded by resorting to debt in such in way that (3.25) become binding. Second (lines 10-19), it attempts to find the optimal borrow (maximum FGV) by repeatedly decreasing a certain percentage (ϵ) of the borrow set in the first step. In this step, the borrow is decreased in a backward movement (starting from period $\mathcal{T}$ to period 1). There are two reasons behind that. First, the probability of bankruptcy is calculated according to the debt ratio at period $\mathcal{T}$. The earlier we borrow, the more we repay. Thus borrowing in the last periods significantly increases the debt ratio (consequently the probability of bankruptcy). Second, due to the time value of money, the tax shield benefit of earlier periods represents more value than the tax shield benefits of the later periods (discounting rate increases in time).

Algorithm 4: FGV Optimization

Input: Inv_t // Investment size at period t
Input: TA_t // Total assets of period t
Input: $loanBalance_1$ // Loan balance of period 1
for $t = 1$ *to* $t = \mathcal{T}$ **do**
  $DebtCap_t = \zeta \times TA_t - loanBalance_t$ // Debt capacity of period t
  if $Inv_t > 0$ **then**
    $borrow_t = Max\ (Inv_t, DebtCap_t)$
    Update $loanBalance_t$ according to constraints (3.19)
  end
end
$FGV^* \leftarrow$ Calculate FGV
$\Delta = 1$
while $\Delta > 0$ **do**
  $FGV_0 \leftarrow FGV^*$
  for $t = \mathcal{T}$ *to* $t = 1$ **do**
    if $borrow_t > 0$ **then**
      $borrow_t = (1 - \epsilon)\, borrow_t$
      $FGV^* \leftarrow$Calculate the new FGV
      $\Delta = FGV^* - FGV_0$
    end
  end
end
Return $borrow_t$ and FGV^*

5.6 Computational experiments

This section details the numerical experiments performed to validate the proposed LNS solution method. Section 5.6.1 details tuning the LNS parameters. Section 5.6.2 clarifies our choice to set the product flows. Then section 5.6.3 reports the results of LNS by drawing a comparison with the Cplex solutions.

5.6.1 Parameters tuning

In our implementation, *shift* and *replace* are equiprobable. This is the same for all removal and repair operators. After preliminary experiments, the swap operator is called every 500 iterations.

In product flows determination, we test the root algorithm parameter in IBM Cplex by solving the relaxed assignment model. There are seven different root algorithms (0: default, 1: primal simplex, 2: dual simplex, 3: network simplex, 4: barrier, 5: shifting, and 6: concurrent). Table 5.3 reports the CPU time consumed for instances of different sizes.

We tested each instance with all Cplex root algorithms three times and report the average value in Table 5.3. Also, the minimum value is highlighted in green. According to this observation, the network simplex is the most efficient one for solving the relaxed assignment model. Thus we choose this algorithm whenever the relaxed assignment model is solved.

In financial decisions determination, ϵ is set to 0.5%. Regarding the acceptance criterion, the initial threshold equals 1.5%. Our experiments show that LNS performs well if the percentage of accepted solutions is between 4% to 15%. The threshold is evaluated and adjusted every 500 iterations to keep the accepted ratio in this range. Following Dumez et al. [2021], if the ratio is below 4%, the threshold is multiplied by 1.5, and if the ratio is above 15%, the threshold is divided by 1.5.

5.6.2 Choosing among the greedy heuristic and the exact approach to set the product flows

As far as the assignment of customers to facilities is concerned, we needed to select either the greedy heuristic or the use of Cplex. We executed the LNS algorithm for some instances using both approaches. The computational time for all instances is set to 1 hour. Each instance is solved 3 times, and the average gap and number of LNS iterations are reported

Instance	Cplex Root Algorithm						
	Default	Primal	Dual	Network	Barrier	Shifting	Concurrent
60 - R - R	0.015	**0.008**	0.012	0.011	0.032	0.070	0.015
60 - C - G	**0.005**	0.008	**0.005**	0.008	0.018	0.054	0.017
90 - R - G	0.033	**0.030**	0.032	**0.030**	0.047	0.115	0.032
90 - C - R	0.020	**0.017**	0.017	0.020	0.040	0.082	0.018
120 - R - R	0.032	**0.028**	0.028	**0.028**	0.054	0.093	0.032
120 - C - G	0.038	0.023	0.038	**0.022**	0.043	0.110	0.033
150 - R - G	0.078	**0.033**	0.057	0.045	0.072	0.303	0.077
150 - C - R	0.087	**0.045**	0.061	0.055	0.078	0.292	0.083
180 - R - R	0.133	0.078	**0.077**	**0.077**	0.093	0.450	0.133
180 - C - G	0.103	0.053	0.053	**0.052**	0.108	0.363	0.075
210 - R - G	0.112	0.108	0.113	**0.083**	0.117	0.457	0.107
210 - C - R	0.120	0.097	0.087	**0.085**	0.133	0.432	0.115
240 - R - R	0.162	0.205	0.122	**0.090**	0.160	0.567	0.155
240 - C - G	0.198	0.142	0.157	**0.138**	0.155	0.550	0.198
270 - R - G	0.138	0.127	**0.118**	**0.118**	0.138	0.567	0.157
270 - C - R	0.173	0.172	0.158	**0.127**	0.220	0.568	0.210
300 - R - R	0.198	0.218	0.173	**0.165**	0.240	0.617	0.182
300 - C - G	0.175	0.198	0.168	**0.152**	0.190	0.553	0.163

Table 5.3 – Comparing CPU time *(in second)* required by each Cplex root algorithm

in Table 5.4.

Instance	Greedy Heuristic		Cplex	
	Gap (%)	# of LNS iterations	Gap (%)	# of LNS iterations
180 - R - R	2.77	308 000	0	35 000
180 - R - G	1.20	303 000	0	40 000
180 - C - R	1.06	295 000	0	41 000
180 - C - G	1.42	291 000	0.18	40 000
210 - R - R	3.85	189 000	0.01	30 000
210 - R - G	1.18	194 000	0.33	27 000
210 - C - R	2.16	211 000	0.03	29 000
210 - C - G	2.30	217 000	0.13	30 000
240 - R - R	3.39	129 000	0	26 000
240 - R - G	2.04	135 000	0.29	23 000
240 - C - R	1.96	129 000	0	26 000
240 - C - G	1.87	136 000	0.02	21 000
Average	2.10	211000	0.08	31000

Table 5.4 – Comparison of the greedy heuristic and Cplex to set the product flows

Column 2 indicates the gap to optimality when greedy approach is employed. Column 3 shows the number of LNS iterations performed in 1 hours when applying the greedy heuristic. Columns 4 and 5 similarly present the same information while solving the relaxed assignment model with Cplex.

Table 5.4 shows that setting the product flows by solving the relaxed assignment model using Cplex performs much better than the greedy heuristic. However, the number of LNS iterations by the greedy heuristic is around seven times higher on average. Yet Cplex leads to a more desirable solution in terms of quality *(Gap is only 0.08 % vs. 2.10 %)*. Thus we choose to solve the relaxed assignment model using the Cplex to set the product flows in each iteration of the LNS algorithm. However,this fast greedy heuristic is still used in the OGV-based repair operator described in Section 5.3.1.2.

5.6.3 Numerical results

All 60 instances introduced in Chapter 4 were solved five times with the LNS algorithm. The maximum computational time is limited to one hour. Recall that in Chapter 4 the maximum computational time for Cplex was 6 hours.

Table 5.5 reports the gap between LNS and the Cplex lower and upper bounds.

Instance	*Gap to (in %)*			
	Cplex Lower Bound		Cplex Upper Bound	
	Best	Average	Best	Average
60 - R - R	—	—	—	—
60 - R - G	—	—	—	—
60 - C - R	—	—	—	—
60 - C - G	—	—	—	—
90 - R - R	—	—	—	—
90 - R - G	—	—	—	—
90 - C - R	—	—	—	—
90 - C - G	—	—	—	—
120 - R - R	—	—	—	—
120 - R - G	—	—	- 0.03	- 0.03
120 - C - R	—	- 0.07	- 0.16	- 0.24
120 - C - G	—	—	- 0.02	- 0.02
150 - R - R	—	- 0.42	- 0.01	- 0.43
150 - R - G	—	—	- 0.02	- 0.02
150 - C - R	—	—	- 0.01	-0.01
150 - C - G	—	- 0.41	- 0.13	- 0.54
180 - R - R	—	- 0.08	- 0.02	- 0.10
180 - R - G	—	- 0.04	- 0.02	- 0.06
180 - C - R	—	—	- 0.03	- 0.03
180 - C - G	- 0.18	- 0.18	- 0.19	- 0.19
210 - R - R	—	- 0.01	- 0.04	- 0.05
210 - R - G	- 0.27	- 0.33	- 0.28	- 0.34
210 - C - R	0.03	0.03	- 0.06	- 0.06
210 - C - G	—	- 0.13	- 0.06	- 0.19
240 - R - R	—	—	- 0.01	- 0.01
240 - R - G	- 1.21	- 1.22	- 1.27	- 1.28
240 - C - R	—	—	- 0.01	- 0.01
240 - C - G	0.05	0.02	- 0.44	- 0.46

Table 5.5 – Comparison of the gap between LNS and Cplex - 1^{st} part

Instance	*Gap to (in %)*			
	Cplex Lower Bound		Cplex Upper Bound	
	Best	Average	Best	Average
270 - R - R	0.02	- 0.02	- 0.16	- 0.21
270 - R - G	0.14	0.06	0.13	0.05
270 - C - R	- 0.28	- 0.37	- 0.29	- 0.38
270 - C - G	- 0.01	- 0.01	- 0.02	- 0.02
300 - R - R	—	- 0.08	- 0.01	- 0.09
300 - R - G	0.03	0.01	- 0.53	- 0.56
300 - C - R	0.08	- 0.14	- 0.79	- 1.01
300 - C - G	0.01	0.01	- 0.02	- 0.02
330 - R - R	0.06	0.06	0.05	0.05
330 - R - G	0.27	0.21	- 7.19	- 7.25
330 - C - R	0.14	0.14	- 4.58	- 4.58
330 - C - G	0.30	0.28	- 1.88	- 1.90
360 - R - R	0.03	0.01	—	- 0.02
360 - R - G	0.08	- 0.10	- 1.25	- 1.43
360 - C - R	—	- 0.09	- 0.01	- 0.10
360 - C - G	0.17	0.15	- 1.67	- 1.69
390 - R - R	- 0.54	- 0.93	- 0.55	- 0.94
390 - R - G	- 0.07	- 0.29	- 3.73	- 3.95
390 - C - R	0.16	- 0.21	- 0.02	- 0.39
390 - C - G	0.35	0.03	- 2.14	- 2.46
420 - R - R	0.60	0.52	- 0.87	- 0.95
420 - R - G	1.21	0.97	- 8.09	- 8.33
420 - C - R	0.39	- 0.34	0.31	- 0.42
420 - C - G	2.07	1.50	- 1.58	- 2.15
450 - R - R	0.03	- 0.18	- 0.09	- 0.30
450 - R - G	0.49	0.29	- 3.81	- 4.02
450 - C - R	1.19	1.19	- 2.86	- 2.86
450 - C - G	2.21	2.14	- 7.63	- 7.69
480 - R - R	—	- 0.38	- 0.01	- 0.39
480 - R - G	0.12	0.03	- 1.39	- 1.48
480 - C - R	0.22	0.05	- 0.91	- 1.08
480 - C - G	0.72	0.64	- 1.99	- 2.07

Table 5.5 – Comparison of the gap between LNS and Cplex - 2^{nd} part

Columns 2 and 3 indicate the best and the average gap *(in %)* between LNS and the feasible solutions found by Cplex (lower bound). Note that in Column 2, we report the best solution among the integrated and the sequential approaches. The " — " symbol is shown whenever the solution found by LNS is the same as the Cplex solution. Negative values express a lower APV obtained by LNS, positive values express a higher APV obtained by LNS.

Columns 4 and 5 present the gap between the LNS and the Cplex upper bound. We can observe a few positive gaps, which correspond to cases where the best solution was obtained by Cplex with the sequential approach. In these special cases, Cplex upper bound can be lower than the unknown integrated optimal solution.

Comparing the LNS solution with the solution provided by Cplex reveals a good performance and stability of the LNS. The average LNS gap to the Cplex lower bound is 0.04% on average and ranges from -1.22% to 2.14%. For most instances with up to 210 customers, the LNS finds the same soluton as Cplex, or solutions with very small gap. For larger instances; LNS outperform Cplex most of the time. All average gaps in column 3 are all larger than -1%, except that of instance 240-R-G.

Figures 5.2 and 5.3 illustrate how the LNS behaves on instances 420-R-R and 420-C-G, respectively. The horizontal axes represent the LNS iterations and the vertical axes the value of the objective function. The Cplex lower bound provided by the integrated and sequential approaches, as well as the Cplex upper bound for the sequential approach (the best among integrated and sequential approaches), are represented by dashed lines. The solid lines represent all 5 LNS executions.

In both cases, LNS rapidly reaches the solution obtained by Cplex with the integrated approach after 6 hours (on average, after around 300 iterations representing less than 3 minutes). It also reaches the solution of the sequential approach after around 1500 iterations for instance 420-R-R, and 1000 iterations for instance 420-C-G (representing around 10 minutes for both cases). This observation shows the ability of LNS to find acceptable solutions in a reasonable time. Moreover, in both cases the five LNS runs go beyond the best solution obtained by Cplex and reduce the gap to the Cplex upper bound. Besides that, the consistent pattern of solid lines shows the stability of LNS in different executions.

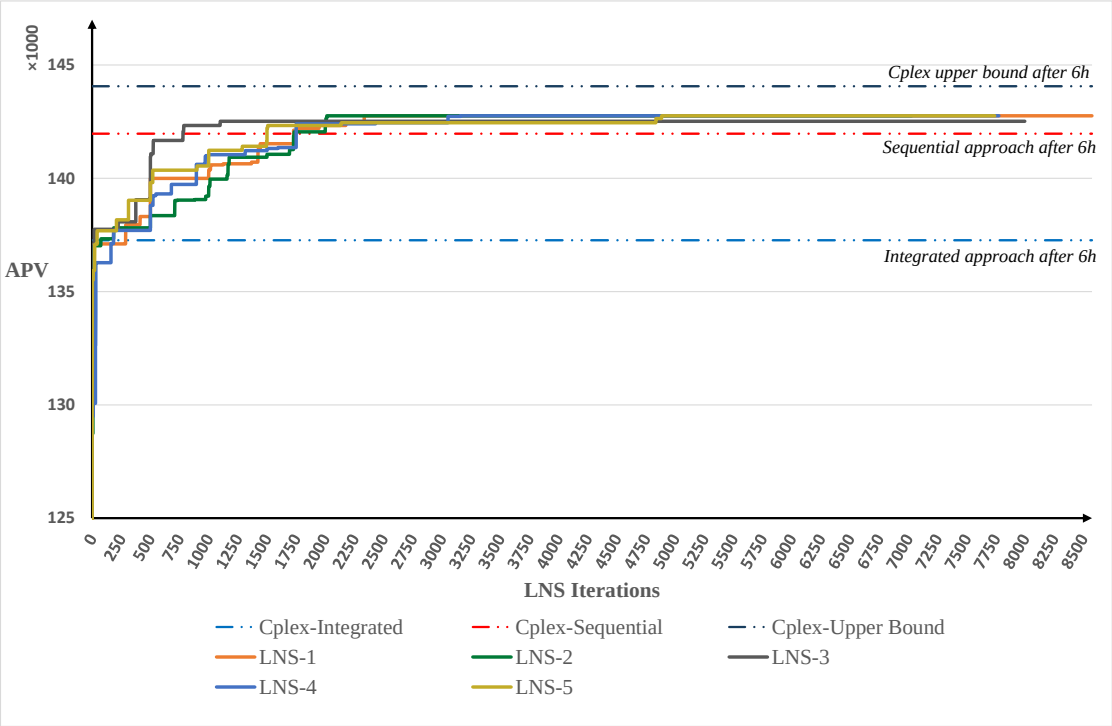

Figure 5.2 – Instance 420-R-R – Comparing Cplex and LNS

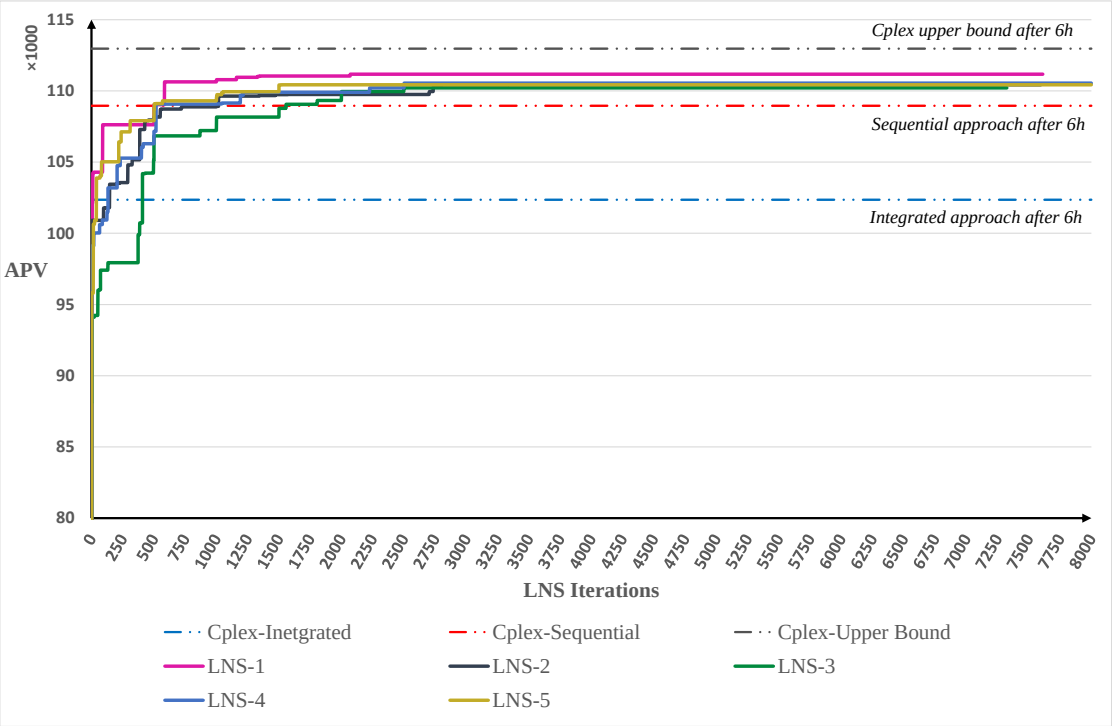

Figure 5.3 – Instance 420-C-G – Comparing Cplex and LNS

5.7 Conclusion

In this chapter, we developed a Large Neighborhood Search (LNS) metaheuristic for the model presented in Chapter 3. To the best of our knowledge, this is the first time that LNS has been used for a dynamic SCND model. Also, this chapter extends the studies that addressed the value-based management in SCND models by proposing a specific solution method.

Each LNS iteration consists of 3 steps. The first one concerns the selection of the set of open facilities as well as their opening times. This is performed through repeated use of removal and repair operators. The customer assignment and product flows are then determined in the second level, by solving a multi-period assignment problem. Two approaches (greedy heuristic and exact approach) have been proposed. The final decision level addressed the financial dimensions of the model for which we have developed a heuristic approach.

We provide extensive comparisons with optimal solutions or bounds obtained by IBM Cplex on the 60 instances introduced in Chapter 4. The numerical experiments show the stability of our LNS framework and its ability to provide high-quality solutions in a reasonable time.

Chapter 6

A Bi-Objective Financial SCND Mathematical Model

In this chapter, we extend the model presented in Chapter 3 to a bi-objective model. To this end, we convert the objective function, i.e., APV, into two conflicting objective functions to be maximized: OGV and FGV. This bi-objective model is first solved with an ϵ-constraint method. Then, we propose a meta-heuristic approach by embedding the single objective LNS (Chapter 5) into a Multi-Directional Local Search (MDLS) framework.

The remainder of this chapter is organized as follows: Section 6.1 gives an introduction to the chapter. Section 6.2 describes the developed MDLS algorithm. The numerical experiments conducted on the MDLS are reported in Section 6.3. Finally, Section 6.4 concludes the chapter.

6.1 Introduction

In Chapter 3, we studied the impacts of financial decisions on logistic decisions by proposing an APV-based SCND model. The APV-based model, consisting of a logistic and a financial segment, simultaneously maximizes the logistics and financial objectives. However, these two desirable objectives are not constantly moving in the same direction, and decision makers could be interested in finding a balance between them. Therefore, this chapter proposes a bi-objective optimization model that separately maximizes logistic and financial decisions. Hence, we consider OGV and FGV as two conflicting objective functions.

Instead of a single solution, multi-objective optimization techniques end up with a set of trade-off solutions, providing decision-makers with adequate options necessary to balance all the fundamental objectives [Guillén-Gosálbez, 2011, Harris et al., 2014].

Employing multi-objective optimization techniques is very common for SCND models that mainly aim at minimizing cost or maximizing profit against improving customer

service levels or reducing environmental impacts. However, these techniques have almost not been used for investigating the value-based SCND problems. There is only the work of Longinidis and Georgiadis [2013] who proposed maximizing the firm's EVA against maximizing the firm's financial performance and credit solvency, measured by the Altman Z-score approach.

Multi-objective models can be solved using MILP solvers or dedicated solution methods (see Table 1.2). However, solving relatively large instances may not be tractable with MILP solvers. Therefore, developing approximated approaches such as the metaheuristic method is inevitable to find trade-off solutions.

There are two main categories of multi-objective solution methods (i) algorithms providing at most one trade-off solution in a single run and (ii) algorithms providing multiple trade-off solutions in a single run. We propose a metaheuristic approach to provide multiple trade-off solutions in a single run. We use the Multi-Directional Local Search (MDLS) framework introduced by Tricoire [2012].

MDLS is a multi-objective optimization procedure employing local search algorithms in a multi-objective framework. The principal idea of MDLS is to successively apply different local searches where each local search applies to one of the objective functions. The procedure provides a set of non-dominated solutions, called a non-dominated set, updated within the solution process. In other words, a local search is used to improve the set of non-dominated solutions respecting each of the objectives separately. An MDLS iteration consists of (i) choosing a solution, (ii) conducting a local search on the chosen solution for each objective/direction, resulting in a new solution in each direction, and (iii) accepting or rejecting the recently produced solutions.

MDLS also enables us to conserve the proposed LNS structure (Chapter 5) by embedding it into a bi-objective framework. We propose to employ a simplified version of the LNS metaheuristic as a local search involved in the MDLS algorithm.

Tricoire [2012] proved the efficiency of the MDLS on several multi-objective problems, such as the multi-objective multi-dimensional knapsack problem, the bi-objective set packing problem, and the bi-objective orienteering problem. Additionally, MDLS is also applied to intermodal train loading planning [Heggen et al., 2018], several variants of the traveling salesman problem [Defryn and Sörensen, 2018], and vehicle routing problems [Kovacs et al., 2015, Molenbruch et al., 2017, Eskandarpour et al., 2019, Lehuédé et al., 2020]. Concerning the SCND models, the MDLS method has been once used by Eskandarpour et al. [2021]. They propose a bi-objective sustainable SCND that aims at minimizing

the network cost and CO_2 emissions. To evaluate the approach, a comparison is drawn between the results obtained by the MDLS procedure and those obtained with Cplex by solving the model employing the ϵ-constraint method. Their numerical results indicate that MDLS outperforms the ϵ-constraint method when the size of instances grows.

6.2 Multi directional local search algorithm for bi-objective SCND

Algorithm 5: The MDLS algorithm for bi-objective SCND

```
1  Initialization of the non-dominated set: P ← P^0
2  while the termination criterion is not satisfied do
3  |   P' ← P
4  |   for every solution p ∈ P do
5  |   |   p_1 = Single-objective local search(p, OGV)
6  |   |   p_2 = Single-objective local search(p, FGV)
7  |   |   P' ← P' ∪ {p_1} ∪ {p_2}
8  |   end
9  |   P ← set of non-dominated solutions in P'
10 end
11 Return P
```

Algorithm 5 describes the main steps of our MDLS implementation. First, a set of non-dominated solutions, denoted by P^0, is generated to initialize the algorithm (see Section 6.2.1). Every MDLS iteration involves exploring the solutions of P by running a local search both for OGV and FGV. This results in a new set of solutions called P' (lines 4-8). Section 6.2.2 explains the choice of single-objective local search methods. The set P' may contain dominated solutions; hence it is first filtered by removing the dominated solutions, and then the resulting set is regarded as the Pareto set at the next iteration (line 9). Lastly, the final Pareto set is returned after meeting the MDLS stopping criterion. One MDLS iteration is depicted in Figure 6.1 as well.

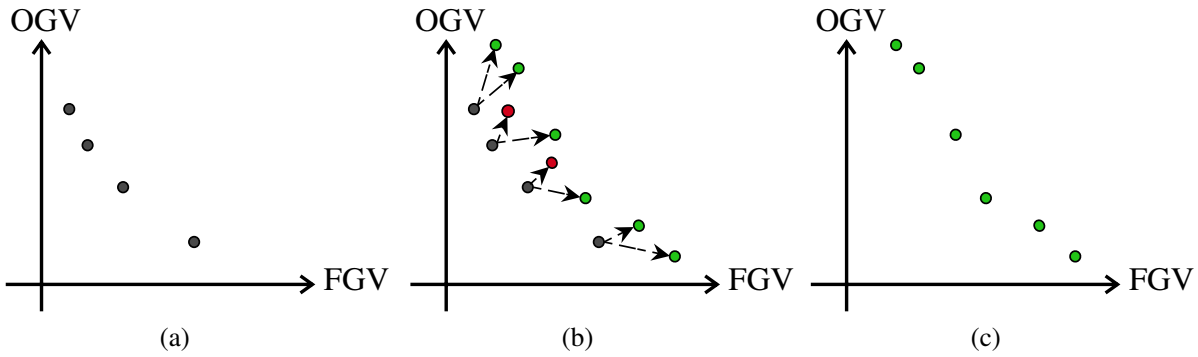

Figure 6.1 – On MDLS iteration. (a) starting set of solutions. (b) Neighbors obtained by MDLS around each solution. (c) Final non-dominated set obtained by filtering dominated solution (in red) [adapted from Eskandarpour et al. [2021]]

6.2.1 Initial non-dominated set

The MDLS algorithm should be initialized with a set of non-dominated solutions that preferably represents adequate diversity of solutions with respect to both objectives. Having a diversified solution set helps the algorithm to explore broad areas of the solution space. We generate a set of random solutions considering different number of facilities varying between $\lfloor \frac{J_{max}}{4} \rfloor$ and $\lceil \frac{J_{max}}{2} \rceil$. For each size, J different solutions are generated by randomly choosing the facilities' set and the opening time. Once the facilities are selected, first the product flows, and then the financial decisions are quickly set using the Algorithms 3 and 4 (heuristic algorithms presented in Chapter 5). Finally a set of non-dominated solutions, denoted by P^0, is selected as the initial solutions.

6.2.2 Single-objective local search

Any local search method can be embedded in the MDLS framework. The Large Neighborhood Search (LNS) is one of the options also proposed in some articles such as Braekers et al. [2016], Eskandarpour et al. [2019], Lehuédé et al. [2020], and Eskandarpour et al. [2021]. In this thesis, we employ single-objective LNS developed in Chapter 5 as the local search method for both OGV and FGV optimization. However, we propose a simplified version of LNS since it is called many times as a local search within the MDLS algorithm. To do so, we slightly alter the operators presented in Chapter 5: (i) the swap operator is no longer used in the MDLS algorithm, (ii) regarding the OGV optimization, the same replace and shift operators are used, and (iii) regarding the FGV optimization, the shift operator remains the same while the replace operator is slightly modified, as described

below:

Removal operators for FGV optimization

1. **Random removal:** It randomly removes a facility from the solution. This helps diversify the search in the solution space.

2. **FGV-based removal:** It specifies an FGV-based score for each operating facility j. Since the FGV contributed by each facility cannot be obtained directly, we use the following procedure to estimate the scores:

   To estimate the score of facility j, denoted by $score_j$, we artificially remove it from the set of operating facilities, leading to a new value of FGV. Then comparing FGVs with and without facility j provides the $score_j$. Note that we assume the borrowing in each period is proportional to the opening cost of each facility. Also, when removing a facility, we assume all the product flows linked to that facility drop to zero.

Repair operators for FGV optimization

1. **Random repair:** It aims at randomly choosing a facility to be added to the solution.

2. **FGV-based repair:** This operator aims to add a facility with a promising FGV. First, FGV estimation is done for the destroyed solution using Algorithm 4 presented in Chapter 5. Then, assuming that the assignment of customers to the operating facilities (in the destroyed solution) remains the same, an assignment is done for the candidate facilities using the greedy heuristic (see Section 5.4.3). Following that, the new FGV is calculated using Algorithm 4. Finally, the difference between two FGVs specifies the $score_j$.

   Once the scores are estimated, the candidate facilities are ranked in a non-decreasing order according to the estimated $score_j$, and one is added to the solution applying the roulette wheel principle.

6.3 Computational experiments

This section details the validation of the developed MDLS solution method through a set of numerical experiments. Section 6.3.1 explains the classical $\epsilon-$constraint (EC) method used to exactly solve the bi-objective model. Section 6.3.4 reports the numerical results obtained by MDLS and the EC method, followed by a comparison of their results.

6.3.1 The $\epsilon-$constraint (EC) method

The EC method is a well-known exact method to solve bi-objective optimization problems (see Table 1.2). This method relies on prioritizing one of the model's objectives: one objective is set as the primary one and the other is integrated in the model's set of constraint. The right-hand side of the corresponding constraint is bounded by some value ϵ. Hence, value of ϵ brings about a distinct MILP model, which can be solved by any MILP solver or solution method. We use the Cplex solver with a time limit of 3 hours for each value of ϵ.

To determine the value of ϵ, we first solve the model once maximizing OGV and once maximizing FGV. It results in two extreme solutions. Then the FGV interval between these solutions is decomposed into nine identical segments,leading to ten distinct value of ϵ [Demir et al., 2014, Eskandarpour et al., 2021]. Thus ten distinct MILPs are solved.

Table 6.1 displays the results obtained by the EC method. Column 2 indicates the number of non-dominated solutions, column 3 reports the total CPU time needed to solve all MILPs, column 4 shows the number of solutions that could not be solved to optimality in 3h, and column 5 denotes the average optimality gap.

Table 6.1 shows the limits of the Cplex in finding the Pareto sets. It only can optimally solve the instances of up to 90 customers. Thus, developing a meta-heuristic algorithm is recommended to provide Pareto sets more efficiently regarding CPU time and solutions' quality.

Instance	Size of non-dominated set	Total time *(second)*	Sub-optimal solutions	Average Gap (%)
60 - R - R	6	1 565	0	0
60 - R - G	5	730	0	0
60 - C - R	6	11 510	0	0
60 - C - G	5	11 186	0	0
90 - R - R	4	5 737	0	0
90 - R - G	5	4 467	0	0
90 - C - R	6	7 392	0	0
90 - C - G	6	26 241	0	0
120 - R - R	7	62 569	3	0.99
120 - R - G	5	74 913	5	1.25
120 - C - R	7	74 586	3	1.18
120 - C - G	6	79 393	4	0.71
150 - R - R	6	83 154	4	1.78
150 - R - G	6	65 373	4	17.74
150 - C - R	4	89 284	6	4.94
150 - C - G	5	99 052	6	14.86
180 - R - R	6	96 428	4	6.80
180 - R - G	3	105 706	8	5.73
180 - C - R	6	93 975	5	8.30
180 - C - G	5	105 416	6	4.44
210 - R - R	5	106 846	7	>100
210 - R - G	5	103 948	6	31.52
210 - C - R	5	105 379	8	>100
210 - C - G	5	102 192	6	82.39
240 - R - R	2	106 821	8	>100
240 - R - G	4	102 322	8	34.89
240 - C - R	5	107 232	8	>100
240 - C - G	5	99 886	7	81.38

Table 6.1 – Results with the $\epsilon-$constraint method - 1^{st} part

Instance	Size of non-dominated set	Total time *(second)*	Sub-optimal solutions	Average Gap (%)
270 - R - R	2	108 000	10	>100
270 - R - G	2	108 000	10	>100
270 - C - R	4	108 000	10	>100
270 - C - G	5	107 325	9	81.38
300 - R - R	6	96 748	6	>100
300 - R - G	6	94 625	5	55.90
300 - C - R	2	106 895	9	>100
300 - C - G	2	107 298	9	>100
330 - R - R	2	106 684	9	52.16
330 - R - G	5	107 493	9	43.24
330 - C - R	6	102 963	6	>100
330 - C - G	3	104 642	8	>100
360 - R - R	2	108 000	10	>100
360 - R - G	5	106 990	9	67.06
360 - C - R	6	99 964	6	74.79
360 - C - G	3	108 000	10	>100
390 - R - R	3	107 204	8	>100
390 - R - G	2	108 000	10	>100
390 - C - R	2	108 000	10	>100
390 - C - G	2	108 000	10	>100
420 - R - R	3	105 624	8	>100
420 - R - G	2	106 601	9	>100
420 - C - R	2	107 939	9	>100
420 - C - G	2	108 000	10	>100
450 - R - R	5	105 688	6	81.96
450 - R - G	3	108 000	10	>100
450 - C - R	2	107 108	9	>100
450 - C - G	2	108 000	10	>100
480 - R - R	2	107 721	9	>100
480 - R - G	5	108 000	10	>100
480 - C - R	2	108 000	10	>100
480 - C - G	3	108 000	10	>100

Table 6.1 – Results with the $\epsilon-$constraint method - 2^{nd} part

Instance	LNS Iterations	
	100	150
60-R-R	229	656
60-C-G	290	513
120-R-G	1045	2563
120-C-R	983	2255
180-R-R	5208	11480
180-C-G	4915	14145
300-R-G	16932	33928
300-C-R	7828	15943
420-R-R	27477	52221
420-C-G	43352	90607

Table 6.2 – Tuning MDLS - CPU time (second) for 100 and 150 LNS iterations

6.3.2 Parameters settings

The parameters of MDLS have been determined based on preliminary computational experiments to keep a good trade-off between the solution quality and computational time. These parameters are the number of the MDLS algorithm and the number of iterations for local searches, i.e., the LNS iterations.

For the MDLS iterations, we first let it run ten times for all solutions of a Pareto set. Note that, in each MDLS iteration, all solutions of a Pareto set are explored. Then for the LNS iterations, we tested this parameter by considering 100 and 150 iterations.

If we consider the Pareto front's quality, considering a larger number of iterations yields slightly better solutions. For instance, Figure 6.2 compares the Pareto sets obtained by 100 and 150 LNS iterations. However, this slight improvement costs more computational time. Table 6.2 shows the corresponding CPU time for 100 and 150 LNS iterations. Thus, To keep a satisfying balance between the CPU time and quality, we choose 100 LNS iterations.

Moreover, we observed that MDLS tends to stabilize after improving the Pareto sets seven times. Thus, considering 100 iterations for LNS (100 for OGV optimization and 100 for FGV optimization), the total number of iterations is 1400. Therefore, in our numerical experiments, we consider that as the number of MDLS iterations.

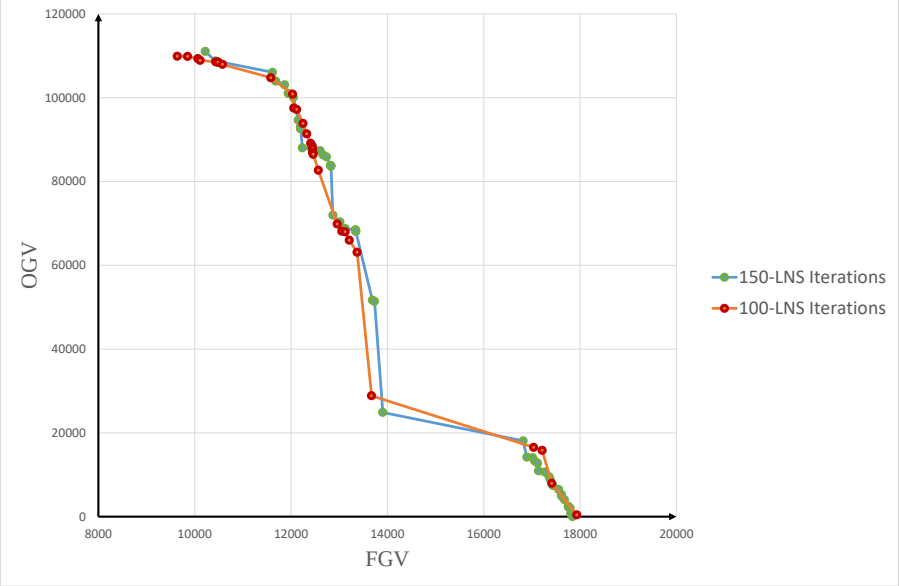

Figure 6.2 – Instance 180-R-R – Tuning MDLS

6.3.3 Performance measures

Measuring the performance of multi-objective optimization algorithms amount to compare the Pareto sets provided by different algorithms, which is not as straightforward as comparing the value of objective functions. Let us consider two Pareto sets P_A and P_B provided by algorithms A and B. It is evident that Algorithm A outperforms Algorithm B if all solutions in P_B are dominated by at least one solution in P_A. Unfortunately, this condition is always never fulfilled. Several measures exist to overcome this difficulty, each measure reflecting one feature of the Pareto sets. Nevertheless, these measures all have some drawbacks. Thus, evaluating the quality using several measures at the same time can provide a fair comparison rather than one single measure [Tricoire, 2012]. This study considers two classical performance measures to compare the MDLS and EC methods.

The unary epsilon indicator The unary ϵ indicator, introduced by Zitzler et al. [2003], represents how far are two Pareto sets from each other. This indicator measures the minimum ϵ value to apply to set P_A so as to dominate set P_B. Mathematically speaking, for a maximization problem with k objectives, a non-dominated solution with the objective

vector $z^1 = (z_1^1, z_1^2, ..., z_1^k) \in Z$ is said to ϵ dominate another non-dominated solution with objective vector $z^2 = (z_2^1, z_2^2, ..., z_2^k) \in Z$ if and only if $\forall 1 \leq i \leq k$, $z_i^1 \geq \epsilon \times z_i^2$, for a given $\epsilon > 0$.

To find such an ϵ, the following formula is used:

$$\epsilon(A, B) = \max_{z^1 \in A} \min_{z^2 \in B} \max_{1 \leq i \leq k} \frac{Z_i^1}{Z_i^2}$$

Note that the smallest possible value of ϵ value is 1, and smaller values are better.

The ratio of approximated Pareto front This indicator, introduced by Altiparmak et al. [2006], shows the percentage of solutions in Pareto set P_A which are not dominated by any solutions in set $P_A \cup P_B$. This ratio, denoted by R, is calculated as follows:

$$R = \frac{|P_A - X \in P_A | \exists Y \in P_A \cup P_B : Y \succeq X|}{|P_A|}$$

where $Y \succeq X$ means solution X is dominated by solution Y.

Note the higher the R, the better the solution set.

6.3.4 Numerical results

The MDLS algorithm has been run five times on all 60 instances presented in Chapter 4. Table 6.3 reports the results and shows the average size of the non-dominated set as well as the average CPU time of the MDLS algorithm and the EC, respectively. Note that the MDLS results are the average of five runs. The results indicate a clear difference in the number of non-dominated solutions obtained: 31.02 for the MDLS and only 4.10 for the EC method. As expected, the MDLS is also much faster than EC. On average, MDLS takes 9 676,4 seconds while EC needs 88 913,1 seconds. Also, with the EC method, most of the instances could not be solved to optimality within 3 hours. Unfortunately, the Cplex lower bound is often very bad, especially for the largest instances. This can explain the small number of non-dominated solutions. To increase the number of non-dominated solutions with the EC method, one option could be to increase the Cplex time limit. Another possibility would be to consider more values of ϵ. In both cases, the computational time would be increased.

Instance	Size of non-dominated set		CPU *(s)*	
	MDLS	EC	MDLS	EC
60 - R - R	8.6	6	175	1 565
60 - R - G	11.6	5	261	730
60 - C - R	10.0	6	226	11 510
60 - C - G	7.6	5	221	11 186
90 - R - R	14.0	4	420	5 737
90 - R - G	13.6	5	414	4 467
90 - C - R	13.4	7	453	7 392
90 - C - G	12.8	6	439	26 241
120 - R - R	13.6	6	711	62 569
120 - R - G	15.8	5	780	74 913
120 - C - R	13.8	7	768	74 586
120 - C - G	14.0	6	874	79 393
150 - R - R	65.4	6	4 789	83 154
150 - R - G	53.6	6	5 349	65 373
150 - C - R	55.6	4	4 263	89 284
150 - C - G	53.2	5	4 172	99 052
180 - R - R	45.6	6	3 916	96 428
180 - R - G	37.6	3	4 475	105 706
180 - C - R	35.8	6	2 248	93 975
180 - C - G	41.0	5	3 810	105 416
210 - R - R	60.6	5	5 172	106 846
210 - R - G	32.2	5	4 790	103 948
210 - C - R	37.4	5	4 816	105 379
210 - C - G	42.2	5	4 441	102 192
240 - R - R	29.8	2	3 700	106 821
240 - R - G	52.4	4	7 506	102 322
240 - C - R	27.8	5	3 982	107 232
240 - C - G	47.2	3	6 938	99 886

Table 6.3 – Comparison between EC and MDLS

Instance	Size of non-dominated set		CPU *(s)*	
	MDLS	EC	MDLS	EC
270 - R - R	34.8	2	5 020	108 000
270 - R - G	29.6	2	6 345	108 000
270 - C - R	52.0	4	10 965	108 000
270 - C - G	42.6	5	12 155	107 325
300 - R - R	38.2	6	6 818	96 748
300 - R - G	51.2	6	12 731	94 625
300 - C - R	23.8	2	6 116	106 895
300 - C - G	29.6	2	7 807	107 298
330 - R - R	16.0	2	8 800	106 684
330 - R - G	22.0	5	11 597	107 493
330 - C - R	18.4	6	11 058	102 963
330 - C - G	20.0	3	12 895	104 642
360 - R - R	27.6	2	8 939	108 000
360 - R - G	49.0	5	13 853	106 990
360 - C - R	32.0	6	7 539	99 964
360 - C - G	46.8	3	13 708	108 000
390 - R - R	30.2	3	13 758	107 204
390 - R - G	49.2	2	18 832	108 000
390 - C - R	22.6	2	12 219	108 000
390 - C - G	26.4	2	15 957	108 000
420 - R - R	15.2	3	20 975	105 624
420 - R - G	19.8	2	26 659	106 601
420 - C - R	15.4	2	27 234	107 939
420 - C - G	21.0	2	33 348	108 000
450 - R - R	31.2	5	22 638	105 688
450 - R - G	29.8	3	21 339	108 000
450 - C - R	31.6	2	28 385	107 108
450 - C - G	36.2	2	24 532	108 000
480 - R - R	28.4	2	17 256	107 721
480 - R - G	44.2	5	26 255	108 000
480 - C - R	35.6	2	16 854	108 000
480 - C - G	25.6	3	17 887	108 000
Average	31.02	4.10	9 676,4	88 913,1

Table 6.3 – Comparison between EC and MDLS

We also evaluate the performance of MDLS and EC using two classical performance measures described above. Columns two and three of Table 6.5 report the ratio of approximated Pareto front, denoted by R. Columns four and five express the value of the unary epsilon indicator. Note that the results of MDLS are averaged over five runs. To measure these two indicators, the Pareto set of each method is compared with a reference set. This reference set is obtained considering the set of all non-dominated solutions provided by either the EC or the MDLS method.

The first indicator, i.e., the ratio of approximated Pareto front, is better with the MDLS approach. On average, R is 0.78 with the MDLS and 0.68 with the EC method. The optimality gaps of EC can explain this. When Cplex cannot find the optimal solutions a for given value of ε, the solutions are dominated by the MDLS solutions. For the small instances, EC generally finds optimal solutions, and thus, the Pareto set dominates that of MDLS. As the size of the instances increases, the EC's ratio decreases.

Instance	R		unary	
	MDLS	EC	MDLS	EC
60 - R - R	0.57	1	1.02	1
60 - R - G	0.60	1	1.15	1
60 - C - R	0.90	1	1.05	1
60 - C - G	0.85	1	1.10	1
90 - R - R	0.92	1	1.02	1
90 - R - G	0.64	1	1.05	1
90 - C - R	0.86	1	1.02	1
90 - C - G	0.42	1	1.06	1
120 - R - R	0.50	1	1.18	1
120 - R - G	0.50	0.80	1.16	1.06
120 - C - R	0.70	0.86	1.05	1.02
120 - C - G	0.31	1	1.15	1
150 - R - R	1	0.17	1	1.43
150 - R - G	1	0.17	1	1.35
150 - C - R	0.97	0.50	1.02	1.32
150 - C - G	0.95	0.20	1.02	1.28
180 - R - R	0.80	0.66	1.06	1.10
180 - R - G	0.80	0.66	1.07	1.09
180 - C - R	0.77	0.66	1.03	1.03
180 - C - G	0.38	0.80	1.12	1.17
210 - R - R	0.94	0.40	1.03	1.17
210 - R - G	0.85	0.60	1.03	1.19
210 - C - R	0.83	0.40	1.07	1.05
210 - C - G	0.77	0.80	1.05	1.01
240 - R - R	1	0.50	1	1.18
240 - R - G	1	0.50	1	1.01
240 - C - R	0.86	0.60	1.04	1.17
240 - C - G	0.76	0.66	1.08	1.06

Table 6.4 – Performance comparison between EC and MDLS

Instance	R		unary	
	MDLS	EC	MDLS	EC
270 - R - R	0.86	1	1.04	1
270 - R - G	0.92	1	1.03	1
270 - C - R	0.90	0.75	1.05	1.12
270 - C - G	0.94	0.60	1.01	1.64
300 - R - R	0.47	1	1.26	1
300 - R - G	0.58	1	1.06	1
300 - C - R	1	0	1	1.12
300 - C - G	1	0.50	1	1.29
330 - R - R	1	0	1	1.09
330 - R - G	0.62	1	1.07	1
330 - C - R	0.26	1	1.19	1
330 - C - G	0.73	1	1.05	1
360 - R - R	1	0.50	1	1.01
360 - R - G	0.83	0.80	1.05	1.04
360 - C - R	0.87	0.66	1.03	1.06
360 - C - G	0.97	0.66	1.04	1.07
390 - R - R	0.66	1	1.15	1
390 - R - G	0.90	0.50	1.05	1.04
390 - C - R	1	0.50	1	1.02
390 - C - G	1	1	1	1
420 - R - R	0.54	1	1.07	1
420 - R - G	1	0.50	1	1.02
420 - C - R	0.96	0.50	1.02	1.08
420 - C - G	1	0.50	1	1.02
450 - R - R	0.95	0.40	1.02	1.05
450 - R - G	0.85	0.33	1.03	1.06
450 - C - R	0.97	0.5	1.04	1.02
450 - C - G	0.97	0.50	1.02	1.06
480 - R - R	0.78	0.50	1.10	1.07
480 - R - G	0.60	0.80	1.08	1.09
480 - C - R	0.85	1	1.07	1
480 - C - G	0.93	0.66	1.03	1.02

Table 6.5 – Performance comparison between EC and MDLS

Figures 6.3, 6.4, and 6.5 depict the Pareto sets of EC and MDLS methods for three sample instances.

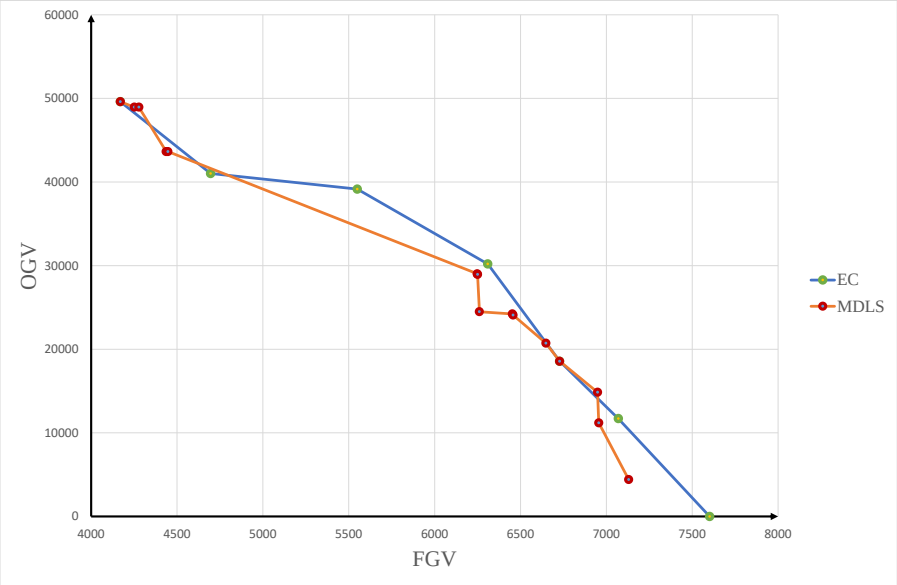

Figure 6.3 – Instance 90-C-R – Comparing EC and MDLS

Generally, two main reasons are behind the behavior of these Pareto sets. By definition, higher FGV corresponds to either higher tax shield benefit, lower expected bankruptcy cost, or both at the same time. First, a higher tax shield benefit can be achieved if debt financing rises. This explicitly implies a higher investment cost. Second, the lower expected bankruptcy cost is correlated with lower OGV. Recall that the bankruptcy cost is a function of OGV; thus, the lower the OGV, the lower the expected bankruptcy cost, and consequently a, higher the FGV.

In order to illustrate the above explanations, we highlighted 4 points in the last figure, i.e., Figure 6.5 to investigate it in more detail. These points were selected according to the slope observed between (A, B) and (C, D) pairs. The main difference between A and B is the number of operating facilities in these two solutions. 14 facilities operate in solution A, while this is 17 with solution B. Moreover, the total investment size of solution A equals 689 200, whereas it is 792 400 for solution B. This higher investment has two consequences. First, it decreases the OGV due to increasing the opening cost.

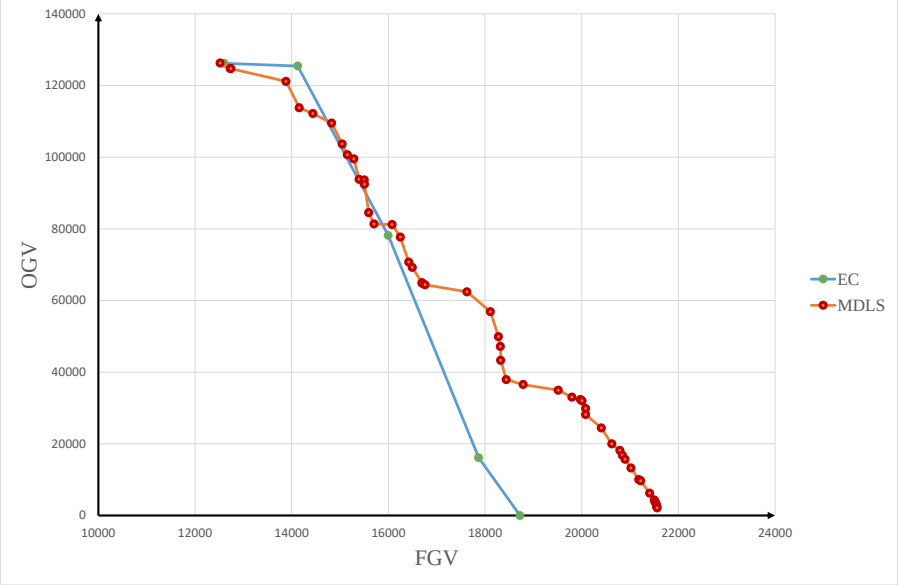

Figure 6.4 – Instance 210-R-G – Comparing EC and MDLS

Figure 6.5 – Instance 360-C-R – Comparing EC and MDLS

Second, it increases FGV by increasing the tax shield benefit and decreasing the expected bankruptcy cost simultaneously. The higher investment of solution B allows more debt financing, resulting in a higher tax shield benefit. Moreover, as the OGV of solution B is lower than A, the bankruptcy cost is smaller; thus, it tends to borrow more. The reason behind the pair of (C, D) is different. The number of operating facilities in both solutions is the same (= 17), while the investment size of solution C is 842 500 rather than 852 100 for solution D. Again, and similar to the former pair, solution D has more opening cost, resulting in lower OGV, and it benefits from more debt financing resulting in a higher tax shield benefit.

6.4 Conclusion

In this chapter, we proposed a bi-objective value-based SCND model that aims at finding a set of solutions respecting logistics and financial priorities. For this purpose, we decomposed APV into OGV and FGV.

The goal was to solve this problem by exhibiting a set of efficient solutions constituting a non-dominated set. We therefore developed a meta-heuristic solution method based on the MDLS framework. We also proposed a simplified version of the LNS structure (presented in Chapter 5) to be employed as a local search within the MDLS algorithm.

In addition to the MDLS, the classical $\epsilon-$constraint method is used to exactly solve the instances. Then, two classical indicators are used to evaluate the results obtained by MDLS and those of the $\epsilon-$constraint method. The numerical results first indicate the inefficiency of the latter regarding both the CPU time and the size of provided non-dominates set. Then regarding the indicators, we observed the outperformance of MDLS, particularly when the size of the instances grows.

However, these results are based on a set of preliminary experiments. Thus there is still some space to be explored. One possible improvement concerns population management. This helps to intensify the search better. Moreover, a path relinking technique could be used to fill the blank area of Pareto sets. Refining the solutions set and setting a limit over the number of active solutions would be interesting as well. It could be obtained by removing the neighboring solutions.

Conclusion

Facility location has been addressed for many years in the management science literature. Classically, models look for a set of locations that seek to optimize an economic function while satisfying a set of constraints (customer satisfaction, capacity, etc.). However, these models have rarely integrated the financing dimensions. Financial decisions are mainly linked to a mixed choice between own investment and loan. In financial theory, this choice turns out to be, among other things, a trade-off between the financial risk of borrowing and tax exemptions. This thesis deals with the impact of financial decisions on the location strategy of a company by integrating logistics and financial decisions in an SCND model.

To this end, we first identified a suitable financial indicator, the Adjusted Present Value (APV), enabling us to answer the principal research question and to take into account the trade-off between tax shield benefit (TSB) and expected bankruptcy cost (EBC). The proposed model is solved following two scenarios: a sequential approach (logistic optimization first, then financial optimization) and an integrated one (single-step optimization). The model is evaluated on a set of generated instances using the Cplex solver. For small-size instances, the problem is optimized thanks to a linearization of several constraints. For large-size instances, we develop a solution method based on Large Neighborhood Search to provide high-quality solutions in a reasonable time. Finally, this work focused on a bi-objective model to analyze some mechanisms separately.

This research includes four major contributions:

(i) Financial theory is full of indicators to assess the value of a company. We proposed to use the Adjusted Present Value (APV) as a financial indicator adapted to the SCND models. APV integrates traditional logistic and financial decisions and enables decision-makers to find trade-off solutions between logistic and financial priorities. It also helps to study the capital structure optimization for firms with either stable or non-stable capital structures. This indicator is also more suitable for financial distress assessment, considering both direct and indirect bankruptcy costs.

(ii) We formulated a mathematical model integrating logistic and financial decisions aiming at maximizing the firm's APV. The proposed model is capacitated, multi-period, single-product, and single-echelon. It determines the optimal network design as well as

the firm's optimal capital structure. The formulated mathematical model contains several non-linear terms. To obviate this issue, a set of linearization procedures are proposed and applied such that the final model is formulated as a MILP model. In addition, an extended planning horizon is defined to capture the long-lasting impacts of financial decisions. Two solution approaches are proposed to better describe the impact of integrating financial and logistic decisions. The first approach solves the whole model in one step, while the second one benefits from decomposing the model into logistic and financial sub-problems and sequentially optimizes the corresponding decisions. The computational experiments indicate that the integrated approach slightly improves the firm value as well as market coverage while it results in a reduction of ROE. Also, they show that for both integrated and sequential approaches, instances of realistic size can be solved to optimality by state-of-the-art MILP solvers; however, the sequential approach is slightly easier to solve.

(iii) We developed a single-objective LNS-based solution method to solve the proposed mathematical model in a reasonable time when the instances size is too large to allow solving the model to optimality. The main LNS framework consists of three sequential decisions: facility location, product flows, and financial decisions. We first set the value of facility location decisions, since they have more global impact than other decisions. These variables are set using the LNS removal and repair operators. Then, a mathematical model inspired by the Generalized Assignment Problem (GAP) is formulated to set the product flows. To solve this model, two different methods are proposed and compared: a greedy heuristic and a relaxed model solved using Cplex. Finally, the financial decisions are set by proposing an efficient heuristic method. The numerical results on a benchmark of 60 generated instances reveal the stability of the LNS algorithm as well as its ability to find high-quality solutions in a reasonable time.

(iv) We extended the single-objective mathematical model presented in Chapter 3 to a bi-objective model. Optimizing logistic decisions and financial decisions are recognized as two conflicting objectives. This helps to deeply study the impacts of financial decisions on the logistic decision. First, an $\epsilon-$constraint method is employed to solve the bi-objective model. Due to its high computational time, we proposed a solution method by embedding the single objective LNS into the MDLS framework. The solution method is tested on a benchmark of 60 generated instances. The numerical results indicate the outperformance of MDLS in terms of the CPU time and the size of non-dominated solutions. Also, the MDLS performance is evaluated by employing two classical performance measures. These measures are calculated for the results obtained by MDLS and those of the $\epsilon-$constraint

method. The comparison reveals the outperformance of the MDLS, especially when the size of the instances grows.

This thesis also opened several research avenues.

(i) As frequently mentioned in the literature, strategic decisions such as network design significantly affect tactical and operational decisions. Considering such decisions enriches the model with further logistic decisions and, consequently, introduces additional financial decisions such as short-term debts and working capital management.

(ii) Since the goal of this thesis is to highlight the interactions between logistic and financial decisions rather than describing one particular supply chain, we considered a simple supply chain with basic logistic rules. Evaluating the impact of additional logistics rules can be interesting. The mathematical model presented in Chapter 3 can be easily generalized to a supply chain with already active facilities, customers, and current loans (initial conditions). Relaxing the incremental customer satisfaction, allowing partial satisfaction of customers, or setting single-sourcing constraints would slightly modify the logistic constraints, but these rules have no impact on the financial part of the model. Similarly, extending the model to more complex supply chains (e.g., with additional echelons, various possible capacities at facilities, and more complex product flows) would require a set of more elaborated logistic constraints, but this would not impact the financial part of the model. However, introducing the possibility of closing facilities has direct financial consequences. A realistic assumption is that once opened, facilities should be operating for a minimum number of time periods (which is generally larger than T). Assuming that facilities operating at period 0 can be closed before the end of their lifetime has several consequences, both on the value of OGV and FGV. Closing a facility and selling it modifies the cash flows. Then, all associated loans must be objects of early reimbursement (with possible financial penalty).

(iii) It would also be possible to test the model of Chapter 3 in a more realistic case where the taxes and interest rates differ from one location to another. This would have no impact on the modeling nor on the solution methods, but this could modify the difference between the sequential and the integrated approaches.

(iv) By nature, risk and uncertainty are inherently associated with financial decisions. Assessing the probability of financial distress is one evident example. However, uncertainty does not only arise in financial decisions. The logistic parameters such as transportation cost and forecasted demand [Pishvaee et al., 2012] can also be subject to uncertainty. Hence, investigating the risk effects is a natural and challenging research direction.

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DOCTORAT BRETAGNE LOIRE / MATHSTIC

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Titre : Conception de chaines logistiques avec intégration de la dimension financière

Mot clés : Localisation ; chaine logistique ; finance ; modélisation mathématique ; recherche à voisinage large

Résumé : Cette thèse porte sur le développement d'un modèle mathématique et d'algorithmes pour optimiser la conception de chaine logistiques, en intégrant des dimensions financières. Nous proposons un modèle multi-périodique, avec contraintes de capacité, sur un réseau à un échelon et avec un produit unique. L'objectif est de maximiser la valeur présente ajustée (APV) de l'entreprise. Les variables de décision binaires sont liées à la localisation des sites logistiques ; les variables continues concernent les flux de marchandises et la planification de la dette. Le modèle mathématique est tout d'abord évalué en résolvant, à l'aide d'un solveur, un ensemble d'instances générées aléatoirement. Nous proposons une approche séquentielle, consistant à optimiser d'abord les variables logistiques, puis les variables financières. Nous décrivons ensuite une métaheuristique de Recherche à Voisinage Large (LNS) pour résoudre des instances de plus grande taille. Enfin, nous considérons le cas où les dimensions logistiques et financières comme deux objectifs indépendants. Nous proposons un algorithme de type Multidirectional local search, utilisant le LNS comme algorithme mono-objectif. Des expériences numériques approfondies évaluent la pertinence de notre modèle et comparent les performances de nos algorithmes à celles du solveur.

Title: Designing a supply chain network integrating financial dimensions

Keywords: Facility location; supply chain; finance; mathematical modeling; large neighborhood search

Abstract: This thesis focuses on the development of a mathematical model and optimization algorithms for the design of a supply chain integrating financial dimensions. We propose a capacitated, multi-period, single-echelon, single-product model. The objective function to be maximized is the firm's value, represented by its Adjusted Present Value (APV). The decision binary variables are related to the location of logistics facilities; the continuous variables concern product flows and debt planning. The mathematical model is first evaluated by solving a set of generated instances using a state-of-the-art solver. We propose a sequential approach, consisting in optimizing the logistic variables first, then the financial variables. Then, we propose an optimization procedure based on the Large Neighborhood Search (LNS) metaheuristic to solve larger instances. Finally, consider the logistic and financial dimensions as two independent objectives. The multi-directional local search (MDLS) is employed to solve the bi-objective model by embedding the LNS into that framework. Extensive numerical experiments assess the relevance of our model and compare the performance of our algorithms to those of the solver.